Generative AI's impact on bank relationship manager roles and customer lending experiences

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A research proposal submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business

Johannesburg, 2025

KEYWORDS

Generative AI, GenAI, Bank Lending, Relationship Manager (RM), Customer Experience

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List of Acronyms

ACRONYM	DESCRIPTION
4IR	The Fourth Industrial Revolution
AI	Artificial Intelligence
DL	Deep Learning
IT	Information Technology
ML	Machine Language
NLP	Natural Language Processing
SME	Small to Medium Enterprise
TAM	Technology Acceptance Model
TOE	The Technology Organisation Environment
UTAUT2	Unified Theory of Acceptance and Use of Technology 2

CHAPTER 1. INTRODUCTION

The chapter outlines the purpose of this study and the associated background that informed the research problem. It articulates the research objectives identified and the rationale for undertaking the research, followed by delimitations of the study. Key terminology used in this study is defined, followed by assumptions that have been made, ending with an outline of the chapter.

1.1 Statement of purpose

This study investigates how South African banks can leverage generative AI (GenAI) technologies to enhance relationship managers' (RMs) customer service delivery in the lending sector. Employing qualitative methods, this study aims to understand how artificial intelligence (AI) can enhance customer interactions and drive organisational success. The diagram presented in Figure 1 illustrates a causal loop reinforcement model depicting the synergy between GenAI technology and its influence on RMs. Advancements in GenAI technology are posited to enhance the competencies of RMs, consequently improving the customer experience. This cycle suggests that customer feedback can inform iterative enhancements in GenAI systems.

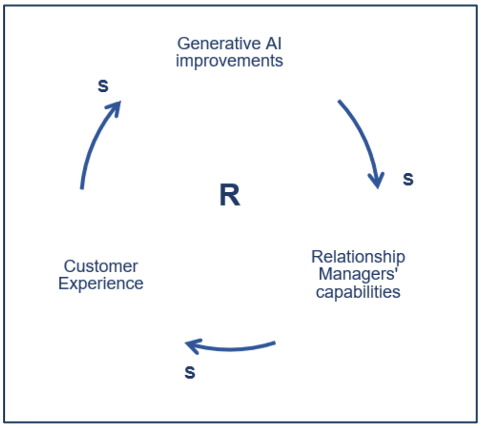

Figure 1: Causal Loop Diagram

Source: Author's own.

1.2 Background of the study

The banking sector in South Africa is undergoing rapid digital transformation, driven by changing consumer expectations and technological advancements (Bansal & Chavva, 2024). With the evolving needs and expectations of tech savvy customers, banks are challenged to innovate and adapt to improve their offerings and stay ahead of the competition.

While traditional AI has been transforming banking operations, the emergence of GenAI presents a distinct paradigm shift in how banks can optimise customer service processes and elevate the customer experience. Domokos and Sajtos (2024) and Donepudi (2017) describe AI as machines that are programmed to mimic human intelligence by analysing data to recognise patterns and make decisions. The authors suggest that GenAI is a subset of AI due to its ability to generate fresh content based on the learned data. In essence, while AI is limited to analysing existing data, GenAI can generate new content from patterns it has learned using AI. By leveraging advanced machine learning (ML) algorithms and natural language processing (NLP) capabilities, GenAI systems can analyse vast amounts of data, extract insights, and generate contextually relevant responses in real-time (ABSA, 2024).

Research conducted by Accenture (Abbott, 2024), analysing over 19,000 banking tasks across 900 job families, found that 73% of banking activities could be enhanced through GenAI - 39% through direct automation and 34% through augmentation. These findings resonate globally, with South Africa included. Mossavar-Rahmani and Zohuri (2023) and Kalia (2023), on the other hand, argue the ethical dimensions of integrating AI into financial services, highlighting the critical need for transparency and accountability in AI systems, particularly in the context of addressing biases and inequalities. This focus on ethical dimensions sparks debate about the potential implications of tools like GenAI on the roles and responsibilities of individuals in financial institutions, notably RMs.

RMs plays a pivotal role in building strong relationships with customers, ensuring their satisfaction and loyalty throughout their interactions with the bank (Hamzah *et al*., 2016). They act as the main point of contact between clients and the institution; handling inquiries, resolving issues, and providing personalised financial advice (Zegullaj *et al*., 2023). By leveraging AI technology, these managers can deliver tailored solutions, anticipate customer needs, and enhance overall satisfaction and loyalty. Miah (2024) argues, however, that while AI tools can improve the efficiency and accuracy of services provided by RMs, they also bring challenges such as the requirement for new skills, potential job displacement, and ethical considerations in decision-making.

Due to limited research on the tangible impact of GenAI in helping RMs provide improved customer service, particularly in bank lending, this study aims to fill this gap and enrich the current body of knowledge on AI technology within the banking industry. The research offers practical guidance for RMs on how to effectively leverage GenAI to elevate the overall lending customer experience.

1.3 Research problem

In financial lending, delivering an exceptional customer experience hinges on RMs' ability to accurately assess creditworthiness, offer personalised recommendations and streamline the lending application process (Zegullaj *et al*., 2023). These RMs, however, often encounter obstacles due to manual processes and outdated systems, leading to extended processing times and decreased customer satisfaction.

Krause (2024) posited that the integration of Generative AI with other cutting-edge technologies is poised to reshape the financial landscape. Accenture (Abbott, 2024) corroborated, stating that GenAI technologies like ML and NLP could potentially revolutionise the way banks analyse customer data, identify patterns and make data-driven decisions. Leveraging these technologies could aid RMs in gaining deeper insights into customer preferences, behaviours and credit risk profiles, enabling them to tailor lending products and services to individual customer needs (Sharma *et al*., 2023). Figure 2 below, extracted from HES Fintech's report on Digital Transformation in Banking and Finance (2020), illustrates how digital advancements lead to enhanced customer service through improved response times. In today's competitive market, banks that do not embrace AI technologies in their lending operations, risk lagging behind and failing to meet the changing needs of their customers (Challoumis, 2024).

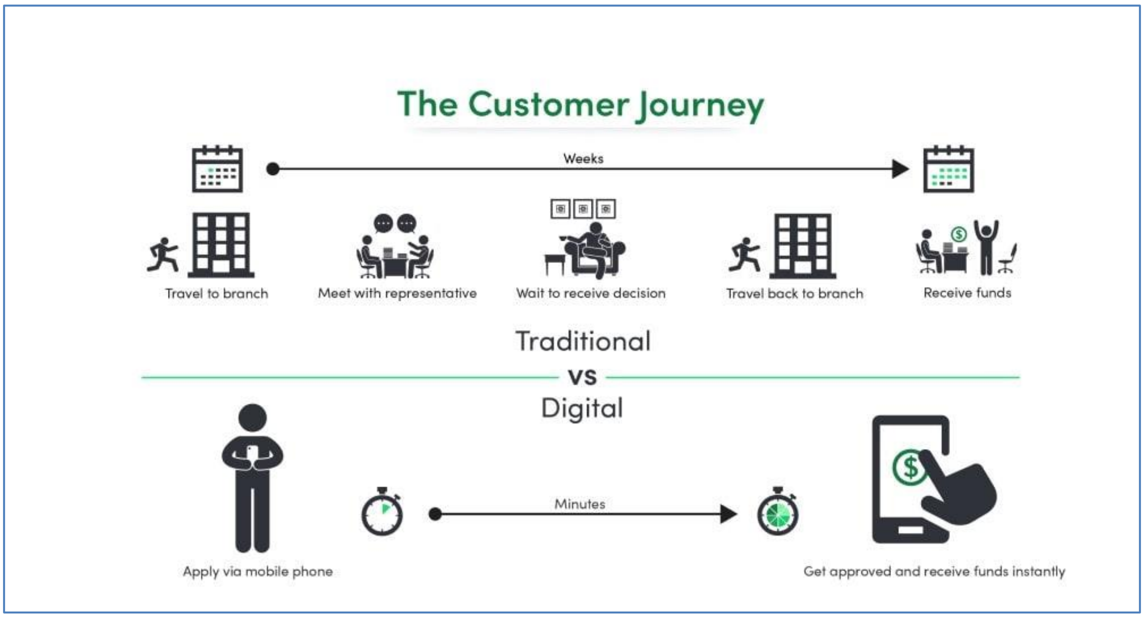

Figure 2: Customer Journey Shift

Source: (HESFintech, 2020)

According to a study conducted by Gyau *et al* (2024), banks that leverage AI technologies in their lending operations can significantly improve customer satisfaction, reduce costs, and increase revenue. Autonomous, an international financial research firm, predicted that AI could help banks save up to $1 trillion in operating expenses globally by 2030 (Abbott, 2024; Joyce, 2024). Abbott elaborated, stating, "our models show that by pairing AI with people to offer personalised wealth advisory, guide commercial relationship conversations, tailor products for individual customers, enhance the quality of contact centre interactions, and streamline their product application and onboarding processes, banks can improve their revenue by 6% or more within three years" (2024, p. 9).

Despite the potential of GenAI technologies to transform lending operations, traditional banks have been slow to adopt. Reluctance can be attributed to regulatory concerns, data privacy issues, and a resistance to change (Oracle, 2021). According to Purdy and Daugherty (2017) only 5% of banks have successfully integrated AI across their organisations, with many citing challenges related to implementation and existing system integration.

While existing literature acknowledges the potential of GenAI to improve banking processes, there is a clear lack of understanding regarding its integration into relationship management roles to enhance the lending customer experience. Studies by Zegullaj *et al*. (2023), Parmar (2023) and Hamzah *et al*. (2016) have all explored AI's impact on RMs ability to improve overall bank customer experience. This gap surfaced the need for empirical research, with practical implementation strategies, to bridge theoretical knowledge presented in the literature. This study aims to fill this gap by investigating how GenAI can enhance RMs ability to deliver personalised and efficient lending solutions, with actionable insights, to optimise the lending customer experience.

1.4 Research objectives

The research objectives of this study to bridge the gap identified in the literature are as follows:

1. To evaluate how GenAI transforms credit lending processes and enables product personalisation in South African banks.
2. To explore how the role of RMs evolves with the adoption of GenAI and its effects on customer experience.
3. To identify the opportunities and challenges of integrating GenAI into relationship management within the banking sector.

1.5 Rationale

The interest in undertaking this research is informed by a critical issue in the banking industry - the need for increased efficiency, accuracy, and personalisation in lending processes to enhance customer satisfaction (Ionascu & Barbu, 2023; ScienceTimes, 2024; Sharma *et al*., 2023). By exploring how GenAI can be integrated into relationship management roles, this research has the potential to offer practical solutions for banks to improve their lending customer experience and stay competitive in a rapidly evolving financial landscape.

Investigating the impact of GenAI on RMs and customer experience in bank lending is relevant because it directly addresses the challenges of manual processes and outdated systems, faced by traditional banks, and the opportunity for GenAI to solve for this (Ek & Arnarp, 2024). By understanding how AI can enhance credit assessment, product personalisation, and customer interactions, banks can leverage technology to streamline their processes, reduce costs, and better meet their customers' needs.

This research addresses the following gaps in existing literature: the lack of empirical studies on the integration of Gen AI into relationship management roles, limited understanding of the evolving role of RMs in the AI era, and the scarcity of research on the practical challenges and opportunities of implementing AI technologies in the bank lending sector. In its attempt to solve for these gaps, this research provides valuable insights into how banks can effectively leverage AI to improve their lending customer experience.

This study contributes to academic knowledge by advancing understanding of how GenAI can transform relationship management roles, enhance theoretical frameworks for integrating AI into the banking sector, and offer empirical evidence on the benefits and challenges of AI adoption. Practically, this research provides banks with a deeper understanding of the implications of GenAI for relationship management practices, enabling them to make informed decisions regarding technology adoption and drive organisational strategy for improved business performance in a digitally driven economy. Policymakers may leverage the findings of this study to formulate regulatory frameworks that promote responsible AI adoption in the banking sector.

1.6 Delimitations of the study

The delimitations listed below serve to clarify the boundaries and focus of this research study:

i. Scope of banking sectors: The research study focuses specifically on the lending sectors within banking institutions. Other sectors within the broader banking industry, e.g., retail or investment banking, have been excluded from the study.
ii. Organisational type: The study targets traditional banking institutions and excludes non-bank financial institutions like credit unions or fintech startups.
iii. Level of employees: The research focuses on RMs and their interactions with customers. Other levels of employees within banking institutions, such as executive management or frontline staff, are not the primary focus of the study.
iv. Conceptual delimitations: The study delimits the exploration of GenAI's impact to relationship management practices within lending sectors, excluding broader applications of AI within banking operations unrelated to customer experience enhancement. Additionally, the study does not delve into individual customer behaviours or preferences, but instead focuses on the overarching trends and implications for relationship management strategies.

1.7 Definition of terms

I. **Artificial Intelligence**: Artificial intelligence, also known as AI, is a type of technology that allows computers and machines to mimic human intelligence and skills in problem-solving (IBM, 2024).

II. **Customer Experience (CX)**: Customer experience refers to the overall perception a customer has of a brand or company based on all interactions and touchpoints throughout the customer journey. It encompasses the customer's feelings, emotions, and opinions formed from various interactions with the company's products, services, and employees. Enhancing customer experience involves improving satisfaction, loyalty, and advocacy (McKinsey, 2021).

III. **Generative AI**: Generative AI or GenAI refers to a subset of artificial intelligence that focuses on creating new or novel content or data that resembles existing data. This can include generating text, images, music, or other forms of media. Generative AI systems use machine learning techniques, often based on models like Generative Adversarial Networks (GANs) or transformer architectures, to produce outputs that are coherent and contextually relevant (McKinsey, 2023).

IV. **Lending Services**: Lending services refer to the financial products and activities offered by banks and other financial institutions that involve providing funds to borrowers with the expectation of repayment, usually with interest. Lending services include various types of loans such as personal loans, home loans, business loans, and credit card loans (Razorpay, 2023).

V. **Machine Learning:** Machine learning (ML) is a subset of AI that focuses on creating algorithms and models that allow computers to learn from data and make decisions or predictions without the need for specific programming for each task. ML algorithms analyse large datasets to identify patterns, relationships, and trends, and use this information to make predictions or decisions. Common ML techniques include supervised learning, unsupervised learning, and reinforcement learning (Oracle, 2024).

VI. **Natural Language Processing**: Natural Language Processing (NLP) is a branch of artificial intelligence (AI) and computational linguistics concerned with the interaction between computers and human (natural) languages. It involves the development of algorithms and techniques that enable computers to understand, interpret, and generate human language data in both written and spoken forms. NLP enables machines to analyse, process, and derive meaning from large volumes of natural language data, enabling applications such as language translation, sentiment analysis, and text summarisation (SAP, 2024).

VII. **Relationship Manager**: A Relationship Manager (RM) is a professional employed by a bank or financial institution who is responsible for managing relationships with clients, typically high net-worth individuals, or business clients. Their role involves understanding clients' financial needs, offering appropriate banking products and services, and providing personalised advice and support (Investopedia, 2022).

1.8 Assumptions

The assumptions below can fundamentally shape the research design, data collection methods, and interpretation of findings. Acknowledging their reasonableness and sensitivity can help reduce biases and strengthen the reliability of the research results.

i. **RMs possess a basic understanding of GenAI and its applications within the banking industry.**

It is reasonable to assume that RMs have a foundational knowledge of emerging technologies within their field. However, the extent of their understanding may vary and could potentially influence their perceptions and responses during interviews or surveys. The outcome of the research is sensitive to this assumption as RMs with limited knowledge of GenAI may provide less meaningful insights or perspectives on its impact on customer experience.

ii. **GenAI adoption within banking institutions is primarily driven by a strategic focus on customer experience enhancement and operational efficiency.**

Given the competitive nature of the banking industry and the increasing emphasis on customer-centricity, it is reasonable to assume that all banks prioritise technologies like GenAI to improve customer experience and streamline operations. The research outcome is sensitive to this assumption as findings that contradict or challenge the assumed motivations behind AI adoption could lead to alternative interpretations of its impact on relationship management and customer experience.

iii. **The perspectives and experiences of RMs sampled for the study reflect standard industry practices and challenges.**

While it is not possible to control for every variation in individual experiences, the assumption that RMs perspectives align with broader industry standards is reasonable given their professional roles and responsibilities. The research outcome is sensitive to the assumption of unique or outlier participant perspectives that are different to industry standards as this could potentially influence the generalisation of the findings.

1.9 Conclusion

The chapter introduced the study's purpose and background, setting the context for the research problem. It outlined the research objectives and reasons for conducting the study, whilst acknowledging any potential limitations. Definitions for important terms were presented, ending with underlying assumptions guiding the research.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

This chapter examines existing literature through three key lenses that are aligned with the research objectives: (1) GenAI's transformative impact on credit lending, (2) the evolution of RM roles, and (3) implementation challenges and opportunities. It introduces and defines the research topic and provides background relevance to the study. Following is an in-depth literature review of the objectives identified in the chapter, as well as inferred propositions that support the research problem. The chapter concludes with a discussion of the analytical framework used in the study.

2.1 Introduction

The literature review begins with an examination of the transformative impact of GenAI in banking and its potential to optimise the credit lending process to provide a more personalised lending experience. Drawing on empirical evidence and industry reports, it examines the impact on enhancing operational efficiency and accelerating decision-making in traditional banking through the automation of repetitive tasks. The literature further analyses how these technology advancements reshape RM responsibilities and the impact this has on customer service. Finally, the literature examines the opportunities of integrating GenAI into the roles of RMs and the challenges that arise thereof.

2.2 Definition of topic or background discussion

The process of digitalisation, known as the fourth industrial revolution (4IR), brought about significant changes in the economy (Adamek & Solarz, 2023), with almost every industry undergoing digital transformation caused by technology advancements. Krijger (2023) argues that the financial industry is no exception, being early adopters to embrace technological advancements like artificial intelligence (AI) due to its potential to transform the industry.

In understanding the impact of 4IR on the financial sector, it is important to first delineate between digitisation, digitalisation, and digital transformation, as these terms are often used interchangeably, yet signify distinct processes. **Digitisation** refers to the conversion of analog information into a digital format, essentially laying the groundwork for digital engagement (Monton, 2022). This foundational step is critical, but it alone does not produce significant change. **Digitalisation**, on the other hand, goes a step further, encompassing the integration of digital technologies into everyday operations, which enables businesses to improve efficiency and enhance customer interactions (Monton, 2022). This process often involves adopting tools and platforms that facilitate faster decision-making and a more streamlined customer experience. Finally, **digital transformation** embodies a more holistic shift, wherein organisations fundamentally rethink their strategies and business models to leverage digital technologies for new value creation (Monton, 2022). This transformation often leads to profound changes in the way businesses operate and deliver value to their customers. With these definitions in mind, it is clear that bank's adopting AI is not merely about leveraging technology but represents a significant shift in how they operate and engage with customers, positioning them favourably in the rapidly evolving landscape of digital services.

The banking sector is traditionally a very data-driven industry and, with the emergence of AI and ML technologies, there is a promise of processing larger volumes of data more effectively. This leverage could fundamentally transform important aspects of banking operations. Recognising the opportunities that AI presents to improve customer experience, streamline operations, reduce costs and make better-informed decisions, its adoption surged in recent years, making the financial industry one of the major adopters of AI (Krijger, 2023).

This transformation is aimed at delivering more accessible, effective and faster banking services through digital technologies (Tad *et al.,* 2023). Sundar Pichai, CEO of Google, was quoted in (Sharma *et al*., 2023, p. 2) as saying, “AI is not a threat to traditional banking; it is a catalyst for its evolution”. Ionascu and Barbu attributed this to “the demands and expectations of increasingly connected and technologically savvy customers (2023, p. 55)”. Banks today offer a range of digital services, including internet and mobile banking, electronic payments, virtual assistant support and revolutionary technologies such as blockchain and AI (Ionascu & Barbu, 2023).

GenAI has now brought us to the brink of a new era – one that will be shaped by automation and innovation, powered by AI (Kalia, 2023). The integration of GenAI technologies into banking services has therefore sparked due interest, with Domokos and Sajtos (2024) attributing it to the potential to boost productivity through process automation, optimisation and innovation, ultimately leading to enhanced customer experience and bottom-line revenue growth. Whilst there are the expected concerns around operational-, regulatory-, reputational- and financial risks, this research has narrowed focus to the evolving role of the RM and explores factors that could further influence adoption to enhance the lending customer experience.

2.3 Generative AI

2.3.1 Definition

It is important to first understand the concept of **AI** before exploring GenAI. Domokos and Sajtos broadly defined AI as “a general concept that refers to the theory and development of computer systems capable of performing tasks that traditionally require human intelligence” (2024, p. 156). Donepudi elaborated, saying, “it is the process of developing intelligent computer software and systems to mimic humans by studying how humans think, how they learn, and their mental ability in solving a problem” (2017, p. 84). DBS Bank captured the meaning succinctly stating, “AI is when the computer is able to independently ‘think’ like a human and perform tasks, while ML is when it 'learns' enough from past data or trends to carry out specific tasks and/or predict future activities" (DBS, 2023, p. 1). Several operational models such as ML, NLP and deep learning (DL) are all used interchangeably to describe AI, but each has a distinct meaning.

Figure 3 below, courtesy of the Boston Consulting Group (BCG), captures these concepts and differences (Riemer *et al.*, 2023).

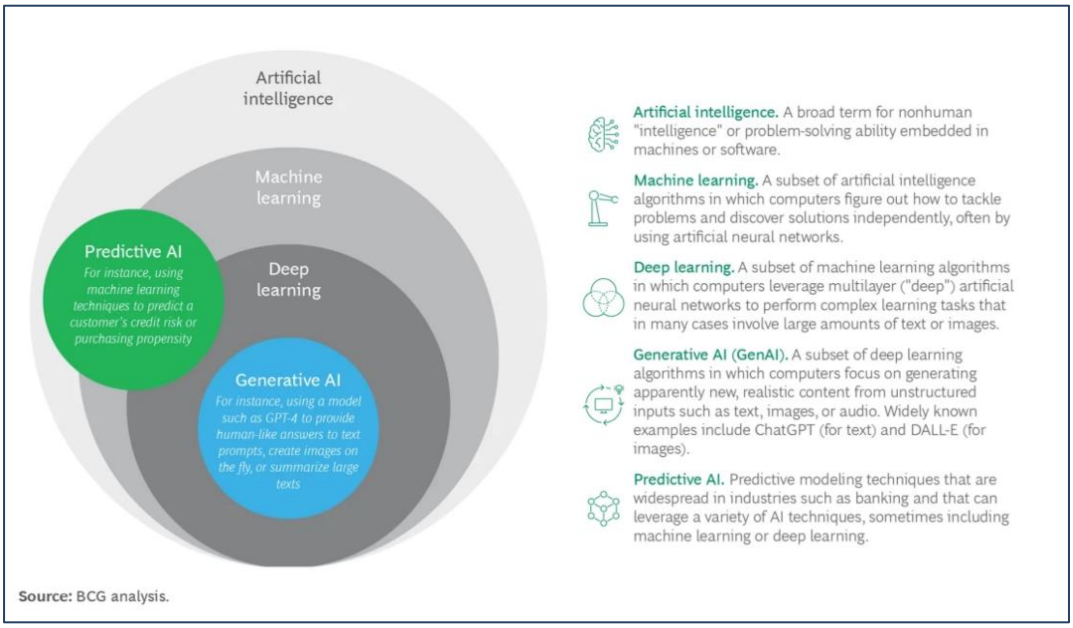

Figure 3: Deciphering the Jargon around AI and GenAI

Source: (Riemer et al., 2023)

Succinctly put, **AI** describes the broad concept of machines imitating human intelligence, while ML and DL are specific methods in this field (Kalia, 2023). Donepudi (2017) defines **ML** as a technique that allows software to analyse historical data to identify patterns and make predictions, which according to Mossavar-Rahmani and Zohuri (2023) is made possible through the availability of large training data sets. **DL**, a subset of ML, aims to simulate the brain's structure using layered neural networks (Emmert-Streib *et al.*, 2020).

GenAI, on the other hand, is a subset of AI which uses ML models to learn from data and create new content (Kalia, 2023; Osei *et al.*, 2023; Tad *et al.*, 2023).

Therefore, instead of relying on current sources like AI does, it is able to anticipate the next step in the pattern it identifies to create new data, images, and other forms of content (Domokos & Sajtos, 2024; Donepudi, 2017). Through training on large data sets, these algorithms progressively understand the characteristics of the various media types they are expected to produce (Krause, 2024). This knowledge allows them to generate new content in the future that is similar to the data they were trained on (Emmert-Streib *et al*., 2020; TechTarget, 2024).

BCG (Riemer *et al*., 2023) observed that while many associate GenAI in banking primarily with customer service chatbots, its capabilities go well beyond that. The authors profess that GenAI can automate financial analysis and assist with code development, with numerous global banks such as Goldman Sachs, Deutsche Bank and American Express, exploring these applications - whether by developing them internally, or using services (Riemer *et al*., 2023).

As financial leaders consider the new opportunities presented by GenAI alongside existing predictive AI solutions, it is noteworthy to recognise that AI applications can enhance nearly every aspect of bank workflows, from customer interactions to backend processes. To effectively leverage GenAI, banks will need to improve their strategies for identifying, prioritising, and nurturing initiatives that will deliver significant value for customers and employees. Big gains from AI happen when banks rethink how an entire process operates, not just the adding of AI in each stage. This means redesigning processes to consider both AI and human roles for the best results. For bank relationship management, this would mean combining GenAI with RM skills, enabling them to work more efficiently and effectively together to create much better results, rather than if they worked separately to achieve the same.

2.4 Transformative potential of GenAI

4IR (Mehdiabadi *et al*., 2020) has brought about unprecedented advancements in technology and transformed the financial sector (Khanchel, 2019). 4IR technologies, such as blockchain, Internet of Things (IoT), and big data analytics, have revolutionised the way financial institutions operate, disrupting traditional business models, and driving innovation in the industry (Shanti *et al*., 2022). These technologies have enabled greater efficiency, improved security, and enhanced customer experiences. The Financial sector, more specifically banking, is undergoing another significant transformation with AI being the catalyst in reshaping traditional operations (Mossavar-Rahmani & Zohuri, 2023) and heralding a new era of efficiencies and customer centric services (Tad *et al*., 2023). Few technologies have evolved at the pace of GenAI - or have the potential to drive such a profound reinvention. Accenture posits that “Leading banks now recognise that the question is no longer *whether* GenAI will transform their industry, but *how*?” (Accenture, 2024, p. 36).

A further international study conducted by Accenture (Abbott, 2024) using data from the US bureau of labour statistics, examined 19,265 tasks in 900 job families across 19 industries, and found that the banking sector would be significantly more affected by GenAI than to other industries. 73% of all banking tasks have a potential to be impacted by AI - 39% have a higher potential for automation, and a further 34% for augmentation (Figure 4). The study concluded that banks that adopt GenAI, can increase their productivity by 30%.

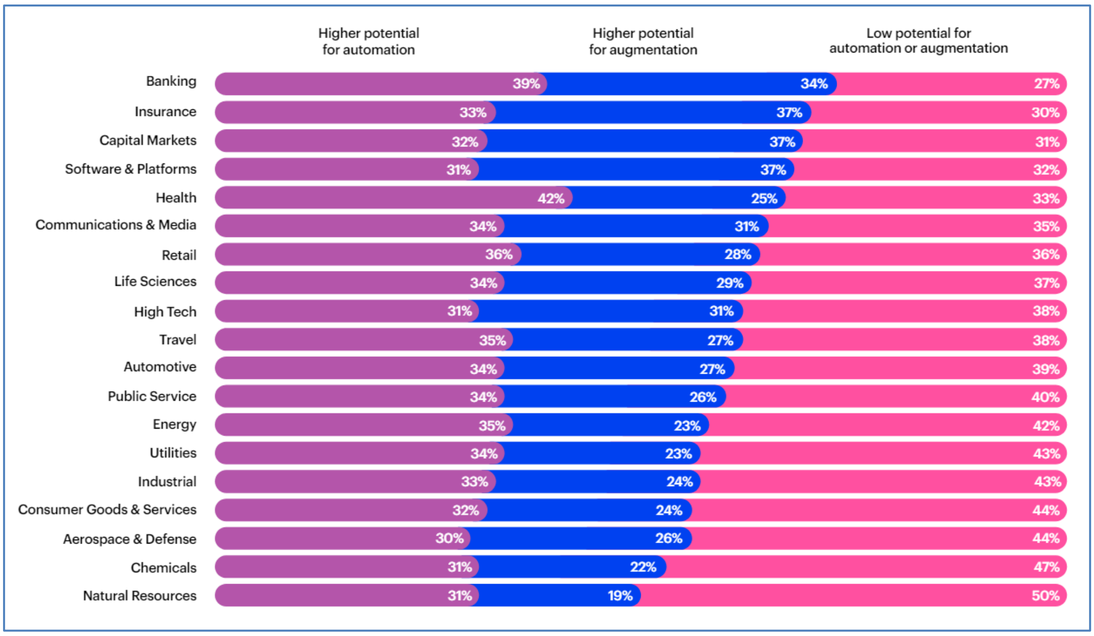

Figure 4: The impact of GenAI on different industries

Source: Accenture (Abbott, 2024)

ChatGPT(2022), an AI-powered NLP tool developed by OpenAI (Sharma *et al*., 2023), was launched on November 30th, 2022 (Banh & Strobel) to enable human-like conversations with a chatbot capable of answering questions and aiding in tasks like composing emails, essays, and code. According to Sharma *et al*., OpenAI utilises Reinforcement Learning from Human Feedback (RLHF) during training, involving testers in scoring and selecting the best outcomes (2023). Key applications include improved operational efficiencies and enhanced customer engagement (Mossavar-Rahmani & Zohuri, 2023). Early adopters like Standard Bank quickly embraced the tool, collaborating with Microsoft to test MS 365 Copilot, which incorporates ChatGPT functionality (ITWeb, 2024). Group CIO, Jorg Fischer, emphasised the bank's commitment to leveraging AI language models to enhance customer service and employee performance. Now, nearly every major bank has adopted a GenAI strategy, conducting their own proofs of concept to explore the potential of AI-driven tools in their operations (Abbott, 2024; Crosman, 2024; ITWeb, 2024; Singh & Singh, 2024).

2.4.1 Automation potential – Credit Assessments

AI and ML technologies can automate various financial processes, including customer service, loan processing, underwriting, risk assessment, and fraud detection (Tad *et al*., 2023). Kayode (2024) advocated that ML algorithms can automate underwriting processes through analysis of large amounts of data to determine creditworthiness, approve loans quicker and eliminate the need for manual reviews. Kalia (2023) corroborated this, adding that analysis of big data, credit history and income amongst other factors, allows ML models to generate more accurate credit risk profiles and optimise the loan approval process. The literature suggests that AI and ML technologies can automate bank lending processes leading to increased accessibility and efficiency of financial services.

Sharma *et al.* (2023) illustrates the various steps in the lending life-cycle that GenAI can support and automate in Figure 5 below.

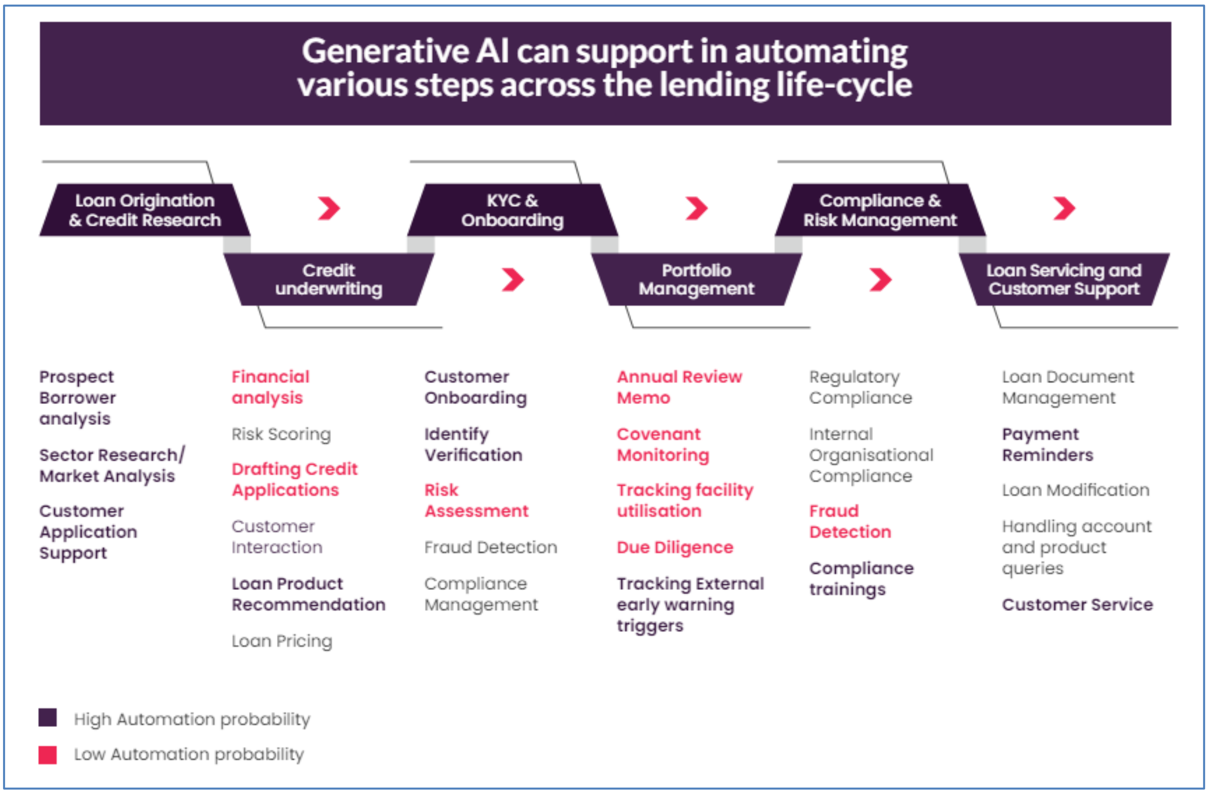

Figure 5: Potential impact of GenAI across the lending journey

Source: (Sharma et al., 2023)

Analysis of the lending life-cycle presented suggest many opportunities for automation:

Lead generation

In the current traditional lending cycle, challenges experienced by RMs with lead generation for bank lending include difficulty in identifying high-quality leads, low conversion rates, and time-consuming manual processes (Palaparthy & Pillalamarri, 2015). GenAI can alleviate these problems by automating lead scoring and streamlining the application process through chatbots (Kayode, 2024), ultimately increasing conversion rates and improving efficiency for bank RMs (Zegullaj *et al*., 2023).

Loan application

Mehdiabadi *et al*. (2020) pinpointed some of the challenges with the current bank loan application process to include the lengthy processing times, high rejection rates, bias in decision-making and limited RM availability for personalised guidance to applicants. GenAI can mitigate by streamlining the application process through automation of various aspects such as document gathering, verification and underwriting (Sharma *et al*., 2023). This can help reduce processing time and increase efficiency. GenAI can further enhance the decision-making process by analysing a broader set of data points to evaluate creditworthiness and improve accuracy in the loan approval decisions (Adamek & Solarz, 2023). This can further reduce rejection rates and ensure fair and unbiased decision-making (Oracle, 2021). Another opportunity would be for GenAI to provide personalised guidance to applicants by tailoring recommendations and advice based on their individual financial situation and needs (Singh & Singh, 2024). This can help applicants better understand their options and make informed decisions.

Credit analysis

Sadok *et al*. (2021) attributed the challenges in lending credit analysis to traditional time-consuming processes, subjectivity - where RMs or loan officers introduce bias into the decision-making process, leading to inconsistent outcomes and; limited data sources. The authors went on to propose that GenAI could solve for time constraints by quickly analysing large amounts of data and providing insights into an applicant's creditworthiness in a fraction of the time it would take a RM or credit analyst. Bhatore *et al*. (2020) further posited that GenAI can help remove bias and subjectivity from the decision-making process by basing decisions on data-driven insights rather than human judgment. The authors suggest that GenAI can integrate data from multiple sources and formats, providing a more comprehensive and accurate view of an applicant's creditworthiness. This could lead to a streamlined credit analysis process and more informed lending decisions (Bhatore *et al*., 2020).

The literature highlights numerous automation opportunities for the use of GenAI and suggests that banks leveraging these capabilities can enhance the overall lending experience for both customers and RMs, leading to more informed and fair lending decisions.

2.4.2 Innovation potential - Product personalisation

AI innovation is reshaping the financial services landscape, as banks embrace cutting-edge technologies to streamline operations and enhance customer experiences. “AI-powered chatbots and virtual assistants enable personalised customer interactions, providing real-time support and assistance with inquiries, account management, and financial planning”, (Kayode, 2024, p. 4).

An example of an innovative implementation is that of PenFed - Pentagon Credit Union (Olavsrud, 2023). PenFed utilised GenAI, with the help of Salesforce's Einstein platform (Parmar, 2023), to revolutionise its customer interactions and significantly improve service efficiency and member satisfaction. This was achieved by deploying chatbots (Kaliuta, 2023) internally and externally. PenFed’s AI journey has yielded impressive results, with a 223% increase in chat and chatbot activity in the past year and a 20% resolution rate on first contact. In a South African context, the opportunities are vast for implementing similar AI technologies for bank lending purposes. By leveraging GenAI like PenFed has done, banks can enhance customer engagements, create more efficient service delivery (Tad *et al*., 2023), and improve customer satisfaction (Singh & Singh, 2024). AI-powered chatbots can streamline loan application processes, provide real-time support to customers (Kaliuta, 2023), and offer personalised assistance based on individual needs.

Additionally, AI can be used to gather data insights (Dhake *et al*., 2024) and analyse customer behaviour, allowing banks to offer more tailored lending solutions (Sharma *et al*., 2023). By leveraging AI to deliver exceptional value to customers (Singh & Singh, 2024), South African banks can stay ahead of the competition and better serve their customers in an increasingly digital world.

The literature suggests that there is significant potential for AI innovation in lending, especially for commercial and retail banks. An opportunity presented by Ooi *et al*. (2023) was for banks to consider developing product or domain-focused GenAI tools to enhance their business operations. This holds huge potential for this research study. What the authors suggest, is that the product or domain of lending services has a significant amount of data sources and can start training ML models with these data sources to develop and provide a platform for personalised consumer engagement. While GenAI is still in its infancy in bank lending sectors, early adopters will stand to benefit significantly in terms of product personalisation, customer satisfaction, and overall business success.

2.5 Relationship management

The banking sector's lending success relies heavily on the individual roles of RMs (Colgate & Lang, 2005). Zegullaj *et al*. (2023) suggested that effective relationship management is crucial for businesses and organisations to build loyalty, trust, and long-term partnerships with their customers and clients.

Therefore, by nurturing these relationships, banks can increase customer satisfaction, customer retention, and ultimately, their bottom line. In a study by Hamzah *et al*. (2016) determining the role of the RM on the impact between customer behaviour and market performance, it was concluded that RMs often find themselves pitted against conflicting expectations; (1) the need to generate revenue for their businesses through sales or utilisation of banking facilities, (2) protecting the bank's interests through due diligence and risk management, and (3) proactively meeting their customers' needs and making sound judgments pertaining to risk and return.

2.5.1 Evolving role in the era of AI – Impact on customer experience

The rapid advancement of digitisation in the banking industry has greatly impacted the traditional role of RMs in bank lending (Colgate & Lang, 2005). As banks continue to embrace technology and automate various processes, RMs are tasked with adapting to new responsibilities and roles to enhance customer experience (Adamek & Solarz, 2023). This shift in focus towards digital solutions has, not only changed the way RMs interact with customers, but also significantly impacted the overall lending customer experience (ScienceTimes, 2024; Sharma *et al*., 2023).

Digitisation has influenced the role of RMs by providing them with advanced tools and technologies to better understand and deliver to their customers' needs (Adamek & Solarz, 2023; HESFintech, 2020). Previously, these advisors spent considerable time manually processing and analysing customer data, relying on traditional Customer Relationship Management (CRM) systems and spreadsheets (Ionascu & Barbu, 2023). GenAI now automates data aggregation, analysis, and insight generation (Dhake *et al*., 2024; Tad *et al*., 2023), allowing RMs to access comprehensive client profiles instantly and focus on strategic activities such as personalised client services. This is made possible through analysis of large amounts of data (Zegullaj *et al*., 2023) and financial planning (Domokos & Sajtos, 2024).

Raj Abrol, CEO of Galytix (2023), a GenAI data technology company, stated in a press release that the company firmly believed in leveraging AI capabilities to assist RMs and credit analysts in banks by automating routine tasks to enhance productivity. “It's like having an analyst on demand" (Galytix, 2023). Thus, by leveraging data analytics and AI, RMs can track customer behaviour, preferences, and transaction history to offer targeted products and services.

Ooi *et al*. (2023) provided the example of a RM inputting a customer’s transactional history into a GenAI model to understand the spending habits, and proposed the offering of a new savings account or product as a personalised service to the customer. In addition, the authors suggested that GenAI models can be used for training RMs, streamlining repetitive and time-consuming tasks, serving as a virtual assistant to respond to customers’ increasingly complex inquiries, as well as releasing staff from routine tasks. The authors proposed that this would allow for more focus on innovative and strategic responsibilities which would lead to increased productivity, efficiency, and accuracy (2023). In an article that examined how GenAI can add value in banking and financial service, Gökhan Sari (2023), head of McKinsey's Financial Services and Risk Practices in Africa, Eastern Europe and the Middle East, suggested using a copilot to assist RMs in delivering improved service. Rather than spending time pouring over vast amounts of information before meeting with a client, the copilot utilises AI technology to analyse client data and provide recommendations quickly. This would allow for more focused and effective client discussions (McKinsey, 2023).

Other use cases that banks are testing include the use of GenAI based virtual assistants to help small-business owners through the loan application process (Chen *et al*., 2023; Khanchel, 2019), as in the case of Bankwell Bank in Connecticut (Crosman, 2024). The Bank partnered with Cascading AI to streamline the small business loan application process (Crosman, 2024). The company’s Casca AI software acts as a virtual assistant named Sarah, to prequalify loans, thus handling the time-consuming, tedious tasks such as data validation and loan approval. This reduced the need for Bankwell’s RMs to spend hours guiding small business lenders through the application process. Sarah runs pre-qualifying tasks with potential lenders 24/7, allowing for faster and more efficient loan approvals. This technology helped to improve the loan application process, resulting in time savings and a more positive overall experience. Bankwell’s case study suggests that GenAI has the potential to revolutionise the way in which RMs respond to customer request and needs. Tad *et al*. (2023) corroborated, stating that GenAI can augment RM capabilities with advanced automation, particularly in complex and resource-intensive processes like small business lending (ScienceTimes, 2024). Additionally, AI's ability to operate autonomously around the clock (Ali & Aysan, 2023), as seen with Sarah handling tasks at late hours, surfaced its role in providing timely and responsive service, which could ultimately improve customer satisfaction and retention (Zegullaj *et al*., 2023).

The literature reviewed suggest that GenAI is reshaping the role of the RM in banking, from transaction processors to trusted advisors, who leverage technology to provide better customer experience and satisfaction (Mossavar-Rahmani & Zohuri, 2023; Zegullaj *et al*., 2023). This includes an understanding of client preferences, financial goals and risk tolerance, allowing them to suggest tailored financial products or investment strategies, thereby offering an elevated client experience.

2.6 GenAI in relationship management

GenAI has exponentiated the potential to revolutionise the way RMs operate within the banking industry (Dhake *et al.*, 2024; Parmar, 2023). Donepudi (2017) suggests that by leveraging ML algorithms these AI systems can analyse large amounts of customer data in real-time and provide personalised recommendations and insights (Bhatore *et al*., 2020). This can lead to more proactive and tailored interactions with customers, improve satisfaction and loyalty (Zegullaj *et al*., 2023) and ultimately increase banks competitive edge in the market (Abbott, 2024). Conversely, Singh (2024) claims that integrating GenAI into RM practices can also present its fair share of challenges, such as concerns over data privacy, ethical considerations, and the need for upskilling and training RMs to effectively utilise these technologies. This section explores the opportunities and challenges of incorporating GenAI into the role of RMs at banks.

2.6.1 Opportunities

2.6.1.1 Personalisation at Scale

GenAI and ML algorithms, not only enable personalised customer experiences by analysing customer data and behaviour (Riemer *et al*., 2023), they also empower RMs to utilise this data and behaviour insights to tailor financial products and services to each client's unique needs. By leveraging these advanced technologies (Parmar, 2023), RMs can strengthen their customer relationships, increase engagement, and ultimately enhance customer satisfaction. Additionally, AI-powered robo-advisors provide automated investment advice (Tad *et al*., 2023), allowing RMs to dedicate their attention to providing tailored and personalised service to clients with more complex financial needs. Overall, the combination of personalised recommendations, automated services, and efficient mobile apps, provided by banks who are equipped with these digital enhancements (Olavsrud, 2023), allows RMs to better serve their clients and deliver exceptional customer convenience (Kayode, 2024).

2.6.1.2 Predictive Analytics

Predictive AI is a type of AI that assists banks with predicting and classifying risks, determining optimal pricing, and modelling product preferences (Riemer *et* *al*., 2023). GenAI and predictive AI serve different purposes, with predictive AI focusing on logic and calculation while GenAI excels in creativity and expression (Devan *et al*., 2024). Riemer elaborated by saying that both are important for a bank's AI strategy as they complement each other like the two halves of the human brain. Predictive AI, like the left brain, handles probabilities and decisions, while GenAI, likened to the right brain, is skilled at generating human-like responses in automated chats (Riemer *et al*., 2023). In order to harness the strengths of both types of AI, a bank's strategy should include both predictive and GenAI with RMs leveraging both to anticipate customer needs and behaviours based on historical data, predict issues or opportunities, and then offer proactive solutions.

2.6.1.3 Intelligence Automation

Automation has been proven to increase productivity and efficiency (Singh & Ahuja, 2024). Robotic Process Automation (RPA), a feature of AI, can automate routine tasks such as data entry and report generation, thus enabling banks to reduce expenditure, simplify operations and free up RMs to focus on strategic activities such as client engagement and problem-solving (Romao *et al*., 2019). Through leverage of RPA, RMs can focus on building stronger relationships with their clients and providing more personalised and efficient service (Romao *et al*., 2019).

2.6.1.4 24/7 Availability

Traditional banking processes involve the manual sorting and analysing of massive amounts of paperwork by RMs, resulting in wasted time and incurring additional costs (Palaparthy & Pillalamarri, 2015). AI-driven chatbots or virtual assistants can provide round-the-clock support (Kayode, 2024), ensuring that customers receive assistance whenever needed, thus improving overall service availability, as in the case study of Bankwell Bank (Crosman, 2024). GenAI, having its expertise in dealing with large data sets, can process large volume of documents , identify important data and summarise this at a fraction of the time and cost it would take a RM (Singh, 2024).

2.6.2 Challenges

2.6.2.1 Algorithmic Bias

The algorithms that power AI services can also introduce complex ethical challenges and one of the most prevalent is the potential to inherit and amplify existing biases (Oracle, 2021). GenAI systems learn from historical data, and should the existing data contain any biases, the system could exacerbate these (Domokos & Sajtos, 2024). From a banking perspective, this could result in prejudiced decision-making in critical financial services, such as lending, insurance, and investment. For instance, if an AI system is trained using biased historical lending information, it could end up unfairly rejecting loan applications from a specific demographic group, thereby reinforcing existing inequities (Matsie, 2023; Oracle, 2021).

2.6.2.2 Skill Gaps and Training

The way in which banks work is about to change fundamentally. According to Singh (2024), innovation is happening globally by skilled people who know how to use GenAI technologies, and who can solve problems using them. E-learning company Coursera claimed that 35 GenAI courses offered by global universities had an intake of 196000 enrolments in India alone in 2023 (Singh, 2024). A study conducted by Accenture (2024) posits that new skills, approaches and mindsets will be needed in every function and level of the bank. The study indicates that recruitment alone cannot solve for the challenges and that a completely new approach to reskilling is required. In context of relationship management roles, this may include upskilling for effective use and interpretation of AI-generated insights. Ooi *et al*. (2023) highlighted a key issue - while GenAI is evolving at a breakneck pace, there is still a lack of understanding as to how such technologies can be integrated into the workplace in a way that generates value. The authors differentiated 2 groups of employees; those that are familiar with GenAI and see the value in utilisation and, those that have little knowledge or are apprehensive about using such technologies (Ooi *et al*., 2023). These distinct divisions may result in conflicts and disagreements, especially in the lending industry, where RMs, who are accustomed to traditional methods (Colgate & Lang, 2005; Ooi *et al*., 2023), may resist new changes and be hesitant to adopt them, resulting in delays in implementation and possible pushback.

2.6.2.3 Customer Acceptance

While automation has its benefits, there have been unwelcome side-effects (Domokos & Sajtos, 2024). According to Accenture's Banking Top 10 Trends for 2024, "by shifting customer engagement out of the branch and onto their digital channels, the banking experience has become functionally correct but emotionally void due to the reduced need for human interaction" (Abbott, 2024, p. 11). As banks' individual and personal connection with customers wane, so too does their ability to differentiate themselves from their competitors (Domokos & Sajtos, 2024), thus making the job market that much smaller (Sharma *et al*., 2023). This is not to discount that some customers may prefer human interaction over AI-driven services, which raises concerns about trust and the personal touch typically associated with traditional banking relationships (Colgate & Lang, 2005) and questions brand loyalty. On average, customers have 6.3 financial products, with only half of them coming from their main bank. 73% of customers have obtained at least one new financial product from a different provider within the last year. (Abbott, 2024).

2.6.2.4 Regulatory Impact

The banking sector is a highly regulated environment where protection of consumer data, adherence to privacy laws, and the maintenance of ethical standards are paramount (BCG, 2023). Banks must address data privacy and protection, maintain security and ensure compliance and accountability. Each of these areas requires careful consideration and adherence to relevant regulations and best practices.

Data privacy and protection: GenAI systems require access to large amounts of customer data to learn and train effectively. This data often includes sensitive information such as financial transactions, personal identification details, and communication history. Ensuring that the data is handled in compliance with data protection regulations is a significant challenge, which includes obtaining explicit consent from customers for data usage and ensuring robust data security measures (Krijger, 2023).

Security risks: Integrating AI into banking operations can heighten cybersecurity risks. GenAI models require robust infrastructure and effective data management, which can complicate a bank's cybersecurity landscape. Financial institutions face stringent cybersecurity regulations that mandate rigorous security measures (Kalia, 2023). Banks must address the implications of AI on their cybersecurity practices. Vulnerabilities in AI systems can lead to data breaches or financial fraud, potentially violating regulatory requirements and undermining customer trust. To mitigate these risks, banks should implement strict security measures, including regular security audits, data encryption, and protection against adversarial attacks. Adhering to regulatory frameworks and specific security standards is essential to safeguarding both the AI systems and the sensitive data they handle.

Compliance and Accountability: Financial regulations demand detailed documentation and accountability for decisions made by financial institutions. When AI systems are used in relationship management, it's crucial to have clear accountability for AI-driven decisions that impact consumers (Abbott, 2024). Banks need to ensure they can audit these decisions, if necessary, which involves maintaining logs of AI interactions and providing explanations and justifications for AI-generated outcomes. Regulators are particularly concerned with identifying responsible parties when AI systems make errors that result in financial losses or breaches of consumer trust. This accountability is essential for maintaining transparency and addressing any issues that arise from AI-driven decisions.

2.7 Analytical framework

The banking sector is undergoing major digital transformation, with GenAI disrupting traditional banking (Ionascu & Barbu, 2023; Kalia, 2023; Khanchel, 2019). This presents a persuasive opportunity for South African banks to optimise customer service and elevate the customer experience through automation and innovation. This research leverages existing theoretical models for a worldview synthesis of information technology (IT) adoption to understand the factors that influence the adoption of GenAI technologies by RMs in bank lending services.

2.7.1 Theoretical Framework

Various technology adoption models were researched, both at an individual and an organisational level.

2.7.1.1 The Technology Organisation Environment (TOE)

The TOE framework was considered at an organisational level as it focuses on the interactions between technology, organisation, and the external environment in determining technological adoption and implementation (Na *et al*., 2022). It considers factors such as technological readiness, organisational structure, and external market conditions. TOE, in context of this research, would be the adoption of GenAI (technology) within the bank lending sector (organisation). External environment would refer to the different customer segments, and regulatory and ethical considerations, for the use of GenAI. Factors such as ease of use, perceived benefits and usefulness, complexity of integration, and IT infrastructure are usually considered relevant in influencing the IT adoption process (Huy *et al*., 2024). These factors are all pertinent to the adoption of GenAI in banking. It is for this reason that the TOE framework has been a proven theory for the study of digital innovation adoption at organisation level and has been validated through several studies (Huy *et al*., 2024; Na *et al*., 2022).

The limitation for adopting the TOE framework for purposes of this research, is that it does not consider the individual in this worldview, i.e., the RM, and would therefore not fulfil the complete research objective. It is for this reason that the model does not suffice for purposes of this research.

2.7.1.2 The Technology Acceptance Model (TAM)

Another theoretical model considered was TAM, which focuses on the individual's perception and attitude toward technological adoption (Na *et al*., 2022). TAM is a widely-used theoretical framework and has been applied in various studies, (Dwivedi *et al*., 2017; Na *et al*., 2022; Venkatesh, 2022), that sought to explain users' acceptance and usage of technology. It emphasises *perceived usefulness* and *perceived ease of use* as key determinants of technology adoption (Dwivedi *et al*., 2017). Perceived usefulness is the belief that a person has that a particular system would improve their job performance. In the context of this research, TAM can be applied to understand how RMs perceive the usefulness and ease of use of GenAI technology in their role (Hamzah *et al*., 2016), and how this perception influences their intention to integrate AI into their practices. This framework can help identify potential barriers to adoption and implementation of GenAI in relationship management, as well as factors that might facilitate its successful integration (Domokos & Sajtos, 2024).

The limitation with TAM though, is that it does not consider the organisation being impacted, i.e., the bank lending sector, and therefore falls short of fulfilling the theoretical worldview required here. It is for this reason that TAM is not used in this research.

2.7.1.3 *Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)*

Unified Theory of Acceptance and Use of Technology 2 or UTAUT2, is a model that helps explain how, and why, people decide to use new technology. It builds on the original UTAUT model of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, and adds 3 more factors – Hedonic Motivation, Price Expectancy and Habit (Dwivedi *et al*., 2017; Venkatesh *et al*., 2012), as shown in Figure 6 below.

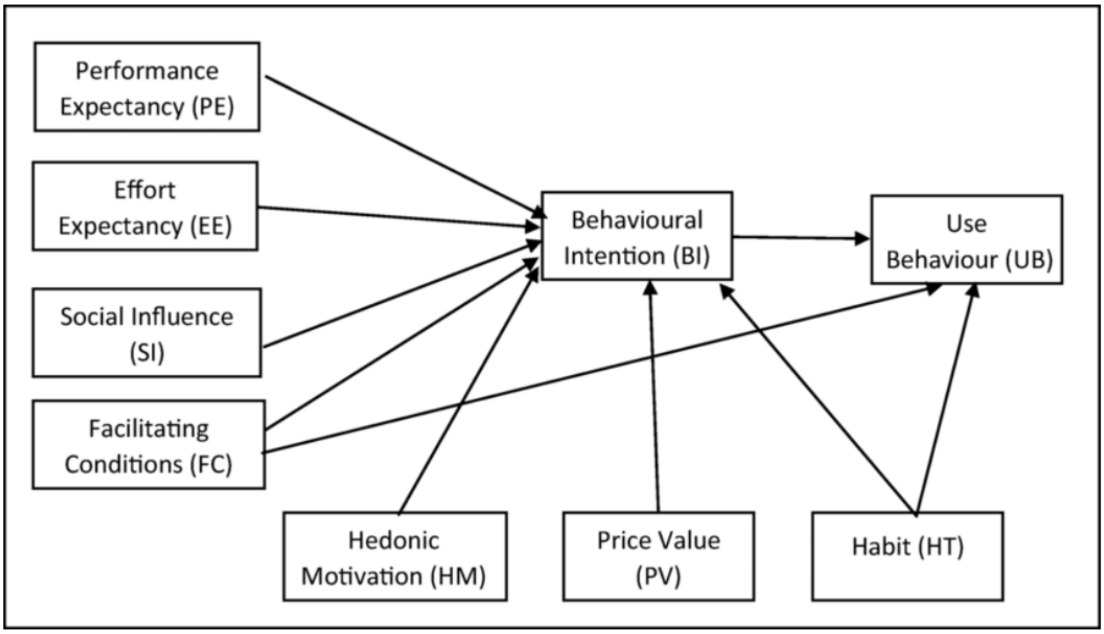

Figure 6: The unified theory of acceptance and use of technology2 (UTAUT2)

Source: (Venkatesh et al., 2012)

Performance Expectancy: This is about how much a person believes that using the technology will help them perform better or achieve their goals (Venkatesh, 2022).

Effort Expectancy: Refers to how easy or difficult a person thinks it will be to use the technology. The simpler it is to use, the more likely they are to adopt it (Dwivedi *et al*., 2017).

Social Influence: Considers how a person is influenced by others around them (like friends, family, or colleagues) when deciding to use a technology. If important people in their lives support the use, they are more likely to use it (Venkatesh, 2022).

Facilitating Conditions: Involves the resources and support that are available to help someone use the technology. Things like training, availability of hardware, or access to the internet are included here (Ayeni *et al*., 2024).

Hedonic Motivation: This is about the enjoyment or pleasure a person gets from using the technology. If it's fun or enjoyable, they are more likely to use it (Dwivedi *et al*., 2017).

Price Value: Considers the cost of using the technology versus the benefits it provides. If the benefits outweigh the costs, people will be more inclined to adopt it (Venkatesh, 2022).

Habit: Refers to the extent to which people automatically engage in using technology as a result of prior actions or experiences. Habit is a critical aspect as, once users become accustomed to using technology, the likelihood of continued use increases even if performance or effort factors fluctuate (Venkatesh et al., 2012).

Behavioural Intention: Pertains to a user's intention to engage with the technology, which is influenced by the other factors in the model. Behavioural intention serves as a direct predictor of actual technology use, as it indicates the user's conscious decision to adopt a particular technology (Dwivedi *et al*., 2017).

Use Behaviour: reflects the actual usage of the technology, capturing how different users engage with the technology in practice. This would help determine if the expected benefits from the adoption of a technology are realised and provide insights into user interactions after the technology has been integrated into the business (Venkatesh et al., 2012).

In essence, the comprehensive nature of the UTAUT2 model, encompassing not only the initial acceptance of technology but also the habitual usage patterns and the transition from intention to actual behaviour, makes it ideal for evaluating the multifaceted impacts of GenAI on customer experience and relationship management in the banking sector. The framework is particularly applicable where technology adoption is influenced by more diverse and nuanced factors such as acquisition of new skill sets, resistance to change and ethical bias associated with the evolving role of RMs in the era of GenAI

The research objectives of the study align closely with the UTAUT2 model for several reasons:

Evaluating Transformation: The model facilitates understanding the complex interplay between technology and users' perceptions in transforming credit lending processes, focusing on key factors like Performance Expectancy and Effort Expectancy, which are central to adopting GenAI.

Evolving Roles of RMs: By incorporating behavioural factors like Habit and Behavioural Intention, UTAUT2 supports examining how RMs integrate GenAI into their practices, helping reveal shifts in professional roles and customer engagement strategies.

Opportunities and Challenges: The model's comprehensive framework allows for a nuanced exploration of barriers e.g., resistance to change, and facilitators of GenAI adoption in relationship management, aligning with the objective of uncovering opportunities and challenges within this context.

Overall, UTAUT2 serves as a robust framework that provides both theoretical grounding and practical insights for this study, focusing on technology acceptance and usage within the evolving banking landscape, thus justifying its selection over other models like TAM and TOE. Again, whilst TAM and TOE are acceptable models, they are limited in that TAM primarily focuses on individual users' acceptance of technology, while TOE is more centred on the organisational context of technology adoption (Na *et al.*, 2022). This study therefore has adopted UTAUT2 as the theoretical framework within which this research is conducted.

2.7.2 Conceptual Framework

The literature review conducted considered some of the most applied theories used in technology adoption, i.e., TOE, TAM and UTAUT2 (Dwivedi *et al*., 2017; Na *et al*., 2022). The conceptual framework of this study is based on the UTAUT2 theoretical model (Venkatesh, 2022; Venkatesh *et al*., 2012). The UTAUT2 model, which identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as some of the critical determinants of technology adoption (Venkatesh, 2022), is particularly relevant to this research. In this context, the adoption of GenAI by RMs is shaped by more nuanced factors, including the evolution of their roles, the need to acquire new skill sets, and their ability to adapt to change. The study therefore seeks to determine whether GenAI plays a mediating or moderating role in influencing the customer experience provided by RMs.

The causal loop diagram, used to set intent for undertaking this research in chapter 1, is referenced again in Figure 7 below as the conceptual framework against which the research problem is explored.

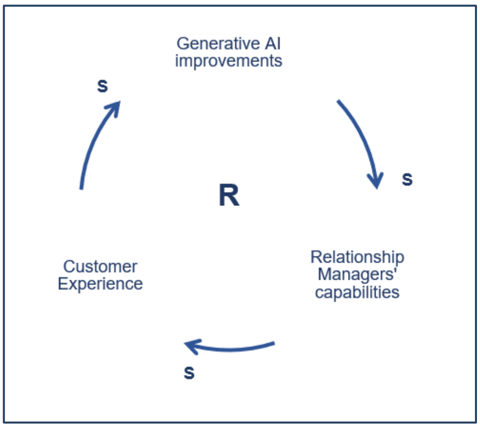

Figure 7: Causal Loop Diagram

Source: Author's own.

The UTAUT2 adoption theory has been mapped against the 3 key variables in the causal loop reinforcement diagram and seeks to establish whether GenAI could effectively influence RMs' ability to enhance the lending customer experience. The research attempts to prove that augmented GenAI technology could boost the skills of RMs, which in turn could lead to better customer experiences. The research also aims to validate the feedback loop theory by aligning the main propositions surfaced in this study within the UTAUT2 theoretical framework, which indicates that customer feedback can enhance GenAI systems. The consistency table presented in Table 1 below aligns each research objective to its mapped proposition, as well as the relevant data collection and analysis methodology utilised in the study.

RO #	Research Objective	Proposition	Data collection detail	Data analysis method
1	To qualitatively analyse the impact of GenAI on the credit lending process and product personalisation in bank lending	**P1**: Through automation and innovative adoption of GenAI technologies, banks can revolutionise their credit lending processes and product personalisation offerings to improve customer satisfaction and drive economic growth.	Interview guide questions (Appendix A1 and Appendix A2)	Thematic analysis
2	To explore how the role of RMs evolves with the adoption of GenAI and its effects on customer experience.	**P2**: Adopting GenAI transforms the role of RMs from transaction processors to trusted advisors, significantly enhancing customer experience through personalised and strategic interactions.	Interview guide questions (Appendix A1 and Appendix A2)	Thematic analysis
3	To identify the opportunities and challenges of integrating GenAI into relationship management within the banking sector.	**P3**: GenAI adoption in bank lending services presents both opportunities and challenges which must be overcome for successful integration.	Interview guide questions (Appendix A1 and Appendix A2)	Thematic analysis

Table 1: Consistency table

Source: Authors own

2.7.2.1 Proposition 1 (P1)

Through automation and innovative adoption of GenAI technologies, banks can revolutionise their credit lending processes and product personalisation offerings to improve customer satisfaction and drive economic growth.

This proposition suggests that banks can enhance the efficiency and personalisation of their services by incorporating automation and GenAI technologies into their credit lending processes and product customisation strategies. This, in turn, can lead to higher levels of customer satisfaction and ultimately contribute to economic growth.

The ways in which GenAI can potentially enhance the efficiency and personalisation of credit lending processes are listed as follows:
Automated credit scoring: GenAI can streamline the credit scoring process by analysing vast amounts of data to accurately assess creditworthiness. This automation can reduce processing times, minimise errors, and improve the efficiency of loan approvals.
Personalised product recommendations: By analysing customer data and behaviour patterns, GenAI can offer bespoke product offerings tailored to individual financial needs and preferences. This level of customisation can enhance the customer experience and drive customer satisfaction.
Real-time decision-making: GenAI can enable real-time loan approvals or rejections based on advanced algorithms that assess risk factors and predict credit outcomes. This can speed up the decision-making process, leading to faster loan processing and improved customer service.

Empirical evidence supporting the above include the research conducted by Sharma *et al*. (2023) on the benefits of GenAI in assessing loan eligibility in the banking sector. The study demonstrated how AI models can accurately analyse customer data, evaluate potential risks, and provide real-time loan evaluations, leading to more informed lending decisions and improved efficiency. Additionally, Singh and Singh (2024) found that AI chatbots, powered by GenAI models, can handle customer enquiries, offer tailored product recommendations, and assist with banking transactions. This can lead to higher levels of customer satisfaction and loyalty. Brown *et al*. (2020), in their study, highlighted the benefits of NLP, including ChatGPT, in enhancing customer engagement, streamlining processes, and improving the overall customer experience in banking. Furthermore, case studies like Bankwell Bank (2024) and Valley Bank (2024) noted the improvements in efficiency, accuracy, and customer satisfaction through the use of AI-powered algorithms for credit scoring and personalised product recommendations.

Figure 8 below illustrates the findings from a joint study conducted by Microsoft Asia and IDC Asia-Pacific, as reported in the Bangkok Post (2019). The results reveal significant improvements reported by financial services organisations that have already begun adopting AI. These include higher margins, better business intelligence, accelerated innovation, better customer engagement and higher competitiveness - recorded in a range of 17% to 26% improvement. This was expected to accelerate to between 35% and 45% after 3 years, an estimated increase of 2.1 times. South African banks have been slower in adoption but there is an expectation to see similar possible trends with the inclusion of GenAI in banking services.

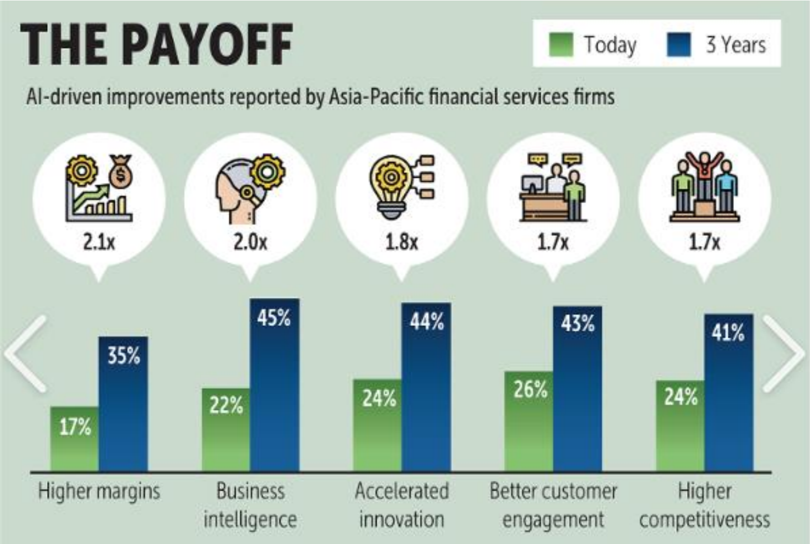

Figure 8: Future Ready Business

Source: (BangkokPost, 2019)

The proposal aligns with the UTAUT2 principles of performance expectancy, effort expectancy, and social influence constructs (Venkatesh, 2022), suggesting that integrating GenAI into credit lending and product personalisation processes, through the use of AI-powered chatbots in banking can optimise operations (performance expectancy), provide tailored recommendations (effort expectancy), and enhance customer experience (social influence). Oracle (2021), however, argued that integrating GenAI into bank lending services could prove to be challenging. The example given was of algorithmic biases in data, resulting in unfair lending practices, which would need to be addressed. Banks would need to implement strategies that guarantee transparency, accountability and fairness in their AI decision-making processes to circumvent this.

From a broader economic perspective, the proposition can have positive impacts on access to credit for SMEs. Leveraging GenAI to streamline their lending process would enable banks can make it easier and faster for small businesses to obtain loans (Crosman, 2024). This can stimulate economic growth, encourage entrepreneurship, and support job creation in the SME sector. By adopting GenAI technologies, banks can differentiate themselves in a competitive market, attract and retain customers, and drive economic growth through more targeted and efficient lending practices.

Challenges relating to the proposition include concerns about data privacy, regulatory compliance, and the potential displacement of human workers. These, however, could be addressed through robust data protection measures (Dhake *et al.,* 2024), adherence to regulatory guidelines, and upskilling of employees to work alongside AI technologies (Zegullaj *et al.,* 2023). The reliability and accuracy of AI algorithms came into question, but the literature argues that advancements in AI technology and ongoing monitoring and evaluation can mitigate these concerns (Kaliuta, 2023).

The proposition that banks can revolutionise their credit lending processes and enhance customer experiences through the adoption of GenAI technologies is supported by existing research, case studies, and practical implications. By leveraging AI to automate processes, personalise products, and empower RMs, banks can drive growth, improve customer satisfaction, and stay competitive in a rapidly evolving industry.

2.7.2.2 Proposition 2 (P2)

Adopting GenAI transforms the role of RMs from transaction processors to trusted advisors, significantly enhancing customer experience through personalised and strategic interactions.

The adoption of GenAI will be driven by the need for a more customer-centric approach in a digitalised banking environment (Zegullaj *et al*., 2023). This shift in role from transaction processor to trusted advisor can enable RMs to provide an enhanced customer experience in multiple ways:
Personalised and proactive recommendations: GenAI will enable RMs to analyse large amounts of data and identify patterns to provide tailored advice to clients (Devan *et al*., 2024). For example, AI algorithms can analyse customer transaction history, spending patterns, and financial goals to offer tailored

recommendations on investment opportunities or loan products to bank lending customers.

Streamlined processes: GenAI can automate routine transaction processing tasks, allowing RMs to focus on strategic advisory functions. For instance, AI-powered chatbots can handle customer queries (Kayode, 2024), freeing up RMs time to engage in more valuable interactions with clients.

Enhanced customer experience: By leveraging GenAI technology, RMs can offer more customised solutions and improve overall customer experience (Hamzah *et al*., 2016). For example, AI-powered tools can predict customer needs and preferences, enabling RMs to anticipate client requirements and provide proactive support.

The practical implications of this proposition are significant for financial institutions and their RMs. By adopting GenAI technology, RMs will have access to robust data analysis tools that can help them better understand their customers' needs and preferences (Hamzah *et al*., 2016). This will allow for more personalised advice and solutions, ultimately leading to better outcomes for the customer.

Empirical evidence supporting this proposition include a study by McKinsey (2023), highlighting how AI can enhance the capabilities of RMs by enabling them to provide bespoke advice to clients. This is accomplished through analysis of large amounts of data and identifying patterns leading to tailored solutions. Furthermore, a recent report by Deloitte (2024) on GenAI and wealth management, discussed how GenAI technology can assist wealth RMs in better understanding their clients' individual needs and preferences, enabling them to offer more customised and valuable recommendations. “Digital solutions augment rather than replace the human element which remains at the core of the industry’s value proposition” (Deloitte, 2024).

Other case studies include those of HSBC (White, 2021) and DBS Bank (2023), who both implemented AI-powered solutions where routine transaction processing tasks were automated. This allowed RMs to spend more time on providing personalised advisory services to clients. The shift in role led to stronger relationships with clients and increased revenue for both banks. These use cases demonstrate AI's ability to improve the speed, accuracy, and efficiency of a number of bank processes, whilst at the same time reduce costs and enhance the customer experience (DBS, 2023; White, 2021).

Appinventiv's graph (2024) in Figure 9 below supports the proposition. The digital IT service provider suggested that the market for GenAI in CRM will grow from $27.1 million in 2024 to $119.9 million by 2032, with the biggest opportunity being automated lead generation.

Figure 9: Market for GenAI in customer relationship management

Source: (Appinventiv, 2024)

The proposition aligns to the adopted UTAUT2 framework as performance expectancy, effort expectancy, and social Influence all play key roles in driving technology adoption. According to the theory, individuals are more likely to accept and use a technology if they believe it will help them perform better in their role (performance expectation), as in the case of Deloitte (2024). UTAUT2 also suggests that individuals would more likely adopt a technology if they perceive it to be easy to use (Miah, 2024) and integrate into their existing processes (effort expectancy). This was demonstrated in the DBS bank case (2023). Social influence also plays a role in shaping individuals' attitudes towards technology adoption. The findings from the studies of McKinsey (2023) and Deloitte (2024) suggest that the use of GenAI technology can augment rather than replace the human element in the RM-client relationship (Miah, 2024). This aligns with the theory that the adoption of AI technology in financial institutions can be positively influenced by social factors such as client trust and relationship building.

One major implication of this evolution is that RMs will need to develop new skills to effectively leverage AI technology. They will need to be trained in data analysis and interpretation, as well as in communication and interpersonal skills to build and maintain trust with their clients (Miah, 2024). Additionally, RMs may need to adapt their workflow and processes to incorporate AI into their daily activities. Focus will need to shift from transactional work to building relationships and providing valuable advice to clients (Zegullaj *et al*., 2023). This shift has the potential to greatly transform their roles, placing a stronger focus on the value they deliver to clients rather than simply the quantity of transactions processed. This change is expected to result in heightened client satisfaction and loyalty, ultimately leading to improved retention rates and increased revenue for banks.

There are, however, potential drawbacks to consider. One concern is the risk of over-dependency on AI technology, which could result in RMs becoming too detached from their clients (Zegullaj *et al.,* 2023). This could erode trust and hinder the development of meaningful relationships. Another is the concerns about data privacy, regulatory compliance, and potential job displacement (Oracle, 2021). Some may argue that the human touch of RMs cannot be replaced by AI technology, and that customers may prefer interacting with a human rather than a machine. Conversely, AI can complement human capabilities and allow RMs to focus on building deeper connections with customers (Deloitte, 2024).

2.7.2.3 Proposition 3 (P3)

GenAI adoption in bank lending services presents both opportunities and challenges which must be overcome for successful integration.

The core components of the proposition involve acknowledging the potential benefits of GenAI adoption in bank lending, such as improved efficiency, enhanced customer experiences, and personalised services (Kayode, 2024; Mossavar-Rahmani & Zohuri, 2023; Sharma *et al.,* 2023). However, it also requires recognising the challenges associated with integrating AI technology, such as data bias, lack of skills and integration challenges with existing systems (Maple et al., 2023; Oracle, 2021). The proposition holds true because it considers the dual nature of AI adoption that must be addressed, i.e., offering opportunities for innovation and growth, while posing challenges for adoption.

The proposition is well supported in empirical research such as a study conducted by Devan *et al*. (2024) which highlighted GenAI's benefits in areas like customer service, personalised banking, credit assessment, operational efficiency and predictive analysis. The research indicates that AI-powered chatbots and virtual assistants have revolutionised customer experience by offering instant tailored suggestions. AI algorithms have been effective in reducing risks in credit assessments and loan authorisations, while automation through AI has enhanced operational effectiveness (Bhatore *et al*., 2020). Predictive analytics has enabled banks to make informed decisions based on data analysis (Emmert-Streib *et al*., 2020). The study has also shown that despite the advantages of AI in banking, there are concerns about ethics and privacy, emphasising the need for careful consideration of issues like data protection and fairness in algorithms (Domokos & Sajtos, 2024). The authors argue that, whilst AI presents opportunities for innovation and increased efficiency in the banking industry, its responsible use is crucial to mitigate risks and promote fairness.

Another case study supporting this proposition, is that of JPMorgan Chase (Weiss, 2017). The bank adopted a GenAI system called COIN (Contract Intelligence) to automate the review of commercial loan agreements. This system helped the bank to process and review loan agreements in seconds, a task that would have taken legal experts 360,000 hours to complete, leading to considerable time savings, enhanced efficiency, lowered operational expenses, and better customer service. Additionally, the system allowed for more customised services by quickly identifying key terms and conditions in loan documents, enabling the bank to offer tailored solutions to their clients.

A key challenge is the issue of bias in AI algorithms. Research has shown that AI algorithms can inherit biases present in the data on which they are trained, leading to discriminatory outcomes (Dhake et al., 2024; Kate et al., 2020; Maple et al., 2023; Oracle, 2021). In the context of lending services, this could result in certain groups of people being unfairly denied loans or offered less favourable terms. The findings of Krijger (2023) supports this proposition by exploring the development of responsible AI practices in the banking industry through a case study of De Volksbank. Krijger highlighted the growing concern around the ethical implications of AI use, an example being the risk of bias, resulting in "AI systems that replicate and exacerbate existing disparities by structurally disadvantaging certain groups" (2023, p. 221). The paper examined De Volksbank's framework as a potential model for effectively implementing AI ethics within organisations. It highlighted the importance of organisational design, interdisciplinary expertise, proactive governance, and high-quality processes in addressing AI ethics which are key considerations for this research study.

A survey of over 500 senior IT leaders undertaken by Goldman Sachs (BCG, 2023), shown in Figure 10 below, highlighted the concerns and challenges with AI adoption in financial services.

Figure 10: C-Suite GenAI adoption concerns and challenges

Source: (BCG, 2023)

According to the survey, 67% of IT leaders planned to prioritise GenAI within the next 18 months - 33% making it their top priority. However, the concerns of data bias, lack of skills and integration with existing systems that were raised, would first need to be addressed and overcome before they would approve adoption (BCG, 2023). Goldman Sachs listed some of their strategies to overcome these challenges as being: compliance with data governance and ethics, using unbiased data sets, using managed AI services and ensuring necessary training of resources (BCG, 2023)

The opportunities and challenges of GenAI adoption in banking services, as highlighted in the studies by Devan *et al*. (2024), JPMorgan Chase (Weiss, 2017) Krijger (2023) and Goldman Sachs (BCG, 2023), can be grounded in the UTAUT2 framework (Venkatesh, 2022). The opportunities of AI adoption such as customer service, credit assessment, operational efficiency, and predictive analysis can be linked to performance expectancy and effort expectancy. The improved customer engagement and operational efficiency provided by AI-driven chatbots and virtual assistants can increase users' performance expectancy, while the automation of processes can reduce the effort expectancy for employees.

The challenges of data bias in AI algorithms, lack of skills and integration with existing systems, can be connected to the constructs of social influence and facilitating conditions. Social influence refers to the impact of social factors on technology adoption, while facilitating conditions refer to the resources and support available to users. In this case, the potential biases in AI algorithms and integration challenges may influence how banks and customers perceive the technology, affecting their behavioural intent to use AI in banking services.

Königstorfer and Thalmann (2020) conducted a literature review exploring the applications of AI in commercial banks and the challenges thereof. The review revealed a lack of focus on AI within the commercial banking sector, despite its potential to revolutionise business operations and enhance customer engagement. The authors highlighted the benefits of AI in reducing lending losses (Sharma *et al.,* 2023), streamlining compliance processes (Dhake *et al.,* 2024), and refining customer targeting strategies (Zegullaj *et al.,* 2023) within commercial banks. However, the literature also identified several obstacles to successful AI implementation, such as maximising technological advantages (Mehdiabadi *et al*., 2020), integrating AI into existing business operations (Mossavar-Rahmani & Zohuri, 2023), fostering user acceptance (Adamek & Solarz, 2023) and addressing data bias concerns (Oracle, 2021). Maximising technological advantages is key as it points to the availability of skilled staff (Mehdiabadi *et al.,* 2020) and the predictive performance of algorithms (Bhatore *et al.,* 2020) as being particularly challenging. The user acceptance challenge speaks to proposition 2 and RMs perception of their evolving role in the era of GenAI, with specific reference to the development of new skills needed to effectively leverage AI technology.

The proposition has practical implications for the banking industry, as it highlights the importance of carefully navigating the opportunities and challenges associated with GenAI adoption. Successful integration of AI technologies can lead to improved customer experiences, enhanced decision-making processes, and increased operational efficiency (Osei *et al.,* 2023; ScienceTimes, 2024). However, failure to address challenges related to data bias, staff training and integration challenges, can result in negative outcomes for banks adopting GenAI (Domokos & Sajtos, 2024; Maple *et al.,* 2023). The researcher argues that the benefits of GenAI (Krijger, 2023; Maple *et al.,* 2023) outweigh the challenges (Königstorfer & Thalmann, 2020; Krijger, 2023; Maple *et al.,* 2023), but it is essential to recognise and address potential drawbacks to ensure successful integration.

Table 2 below, graphically depicts how each research proposition was mapped against its determining UTAUT2 construct based on the literature findings as discussed in this section.

	Proposition 1	**Proposition 2**	**Proposition 3**
Performance Expectancy	• Enhance credit lending processes • Product personalisation	• Personalised and strategic interactions • Transforming role of RM	• Opportunities – Credit assessments • Opportunities – Customer service • Opportunities – Operational efficiencies • Opportunities – Predictive analytics
Effort Expectancy		• Transforming role of RM	• Challenges – RM lack of skills • Challenges - Integration
Social Influence	• Customer experience	• Customer experience	
Facilitating Conditions			• Challenges – Data bias • Challenges -Upskilling RMs
Hedonic Motivation	• Customer experience	• Customer experience	
Price Value	• Operational efficiencies, Revenue growth		• Operational efficiencies • Revenue growth
Habit			

Table 2: Research proposition alignment to UTAUT2 framework

Source: Author's own

P1 aligns with the UTAUT2 principles of *performance expectancy, social influence, hedonic motivation* and *price value* constructs (Venkatesh, 2022), which suggest that through integration of GenAI into lending processes, banks can enhance customer experience, optimise operations and ultimately grow revenue.

P2 maps to the *performance expectancy, effort expectancy, social Influence*, and *hedonic motivation* constructs, suggesting that RMs are more likely to accept and use GenAI technology if they believe it will help them perform better in their role - *performance expectancy* (Deloitte, 2024), and if they perceive it to be easy to use and integrate into their existing processes - *effort expectancy* (Miah, 2024). The findings also reveal GenAI could enhance operational efficiencies (Miah, 2024) resulting in an enhanced client experience which would foster loyalty and trust - *social influence*.

P3 suggests that the opportunities of AI adoption i.e., customer service, credit assessment and operational efficiency, predictive analytics, can be mapped back to *performance expectancy, effort expectancy* and *price value*, whilst automation of processes can reduce *effort expectancy*. The challenges with AI adoption, i.e., data bias, lack of skills and integration issues can be linked to the constructs of *effort expectancy* and *facilitating conditions*.

2.8 Conclusion

This chapter provided an overview of the literature on GenAI in the banking sector. It further discussed the evolving role of the RM in the digital era. The chapter then focused on the opportunities and challenges of integrating GenAI into the relationship management role in banks. The chapter went on to discuss the theoretical framework and its suitability for the research study, ending with an outline of the conceptual framework that will be used to inform the research.

The next chapter outlines the research methodology used in this study.

CHAPTER 3. RESEARCH METHODOLOGY

This chapter discusses the methodology to be conducted in addressing the research objectives. The chapter begins by outlining the research paradigm, research approach and design that will be applied to this study. It then describes the data collection methods, data collection instruments, sampling methods and data analysis strategies that will be applied. Focus shifts to the limitations of the study and quality assurance that will be utilised. The chapter ends by discussing ethical issues that need consideration and timelines for undertaking the research project.

3.1 Research Paradigm

The research paradigm chosen for this study is **interpretivism** of an inducive nature, which emphasises understanding the significance and interpretations that individuals attribute to their experiences (Ugwu *et al.*, 2021). This suggests that individuals' perspectives and beliefs play a crucial role in shaping their behaviours and actions (Bhattacherjee, 2012). The author argues that researchers aim to understand these subjective interpretations rather than seeking objective truths or general laws. What interpretivism will lend to this study is the ability for the researcher to provide deep insights into RMs experiences through the interpretation and analysis of qualitative data such as interviews, observations, and documents. This can help in unearthing the underlying motivations, attitudes, and behaviours of RMs towards the use of GenAI in their roles, providing rich insight into the topic. This understanding supports the research objective of examining how the role of RMs is affected by the implementation of GenAI and its impact on customer experience within the banking industry.

Interpretivism suggests that reality is subjective and socially constructed (Ugwu *et al.,* 2021). The **ontology** in this research project would therefore be realistic as it focuses on understanding the objective reality of the impact of GenAI on bank lending and customer experience. It acknowledges that there is a tangible impact of technological advancements in the banking sector. This means that the experiences and interactions between RMs, their customers experiences and AI technologies are shaped by their individual interpretations and perceptions. By using an interpretivist approach, researchers can explore how these subjective experiences influence the effectiveness and success of integrating GenAI into the role of relationship management.

Interpretivism emphasises the importance of understanding the meanings and interpretations that individuals assign to their experiences (Ugwu *et al.,* 2021). The **epistemology** in this research project would therefore be a combination of constructionism and pragmatism. Constructionism can help in understanding the evolving role of RMs in the context of GenAI, while pragmatism can help in identifying practical solutions to integrating AI into relationship management practices through qualitative research methods such as interviews and observations.

Interpretivism acknowledges the influence of values and beliefs on research and recognises that researchers' own biases and perspectives can shape the research process and outcomes (Bhattacherjee, 2012; Turner, 2010). The **axiology** in this research project would therefore be value laden as this researcher must remain aware of own values and beliefs and how these may influence the interpretation of the data collected. Acknowledgement of own biases allow researchers to present a more balanced and nuanced understanding of the research objective and outcomes (Turner, 2010). This could be considered a possible limitation of the interpretivism paradigm. The limitation here is that the researcher's own biases and preconceptions could influence the outcomes of the research and make it difficult to achieve objective and generalisable results. To mitigate the above and enhance the reliability and credibility of the research findings, the researcher will employ multiple data sources and triangulation methods. This will include comparing data gathered from interviews with RMs and solution architects, who will also be interviewed in this study. This approach aims to provide a more nuanced perspective, as the architects hold a broader, more strategic oversight. Triangulation may also entail analysing and contrasting information gathered from interviews, meeting transcripts, and AI-generated notes to uncover shared trends and themes across varying data sets. The researcher will adopt reflexivity throughout the research process to further ensure the rigour of the findings, by being self-aware of own assumptions, biases, and perspectives that may influence the interpretation of the data.

3.1.1 Research approach

Qualitative research is employed as the research methodology for this study (DiCicco-Bloom & Crabtree, 2006). Research methodology refers to the methods used to collect, analyse, and interpret data for research studies (Dehalwar & Sharma, 2023). The two methods for conducting research are: qualitative research, which is constructed using non-numerical data such as interviews, observations, and open-ended surveys, and which this study has utilised; and quantitative research, which is constructed using numerical data such as structured surveys, experiments, and statistical analyses (Verma *et al.,* 2024).

The qualitative approach is based on the assumption that by gathering rich, detailed data through interviews, observations, and analysis of documents, the researcher can gain insights into complex situations and events and capture the perspectives of stakeholders involved (Dehalwar & Sharma, 2023). Subscribing to this approach affords the researcher the opportunity to gain deeper insights into the research phenomena (Verma *et al*., 2024), which in this study is the evolving role of the RM in the era of GenAI. It allows the researcher to critically study the attitudes, motivations, and behaviours of the evolving roles of RMs and the implications to customer experience.

The literature also suggests that the qualitative approach provides the flexibility and adaptability (Dehalwar & Sharma, 2023) needed to navigate the complexities of the research topic and enables the researcher to uncover unexpected insights and patterns in the data. This holistic approach has the added benefit of allowing the researcher to adapt to emerging themes and to generate new hypotheses and theories based on the data collected.

Whilst the qualitative approach is the most suitable for this research study, there are some challenges with its use. One of the challenges is the subjectivity and bias in data interpretation as qualitative research relies on the researcher's judgment and interpretation of the data (DiCicco-Bloom & Crabtree, 2006). The researcher's world view of GenAI, as an example, could influence the feedback. Another issue is the limited generalisability of findings (Turner, 2010) as qualitative research typically focuses on a small sample size and may not be representative of the broader population of RMs in bank lending. There is also the risk of missing data, especially if the participants do not fully understand the question, and this could potentially require a larger target population (DiCicco-Bloom & Crabtree, 2006). Furthermore, data collection and analysis, is by nature, time-consuming and often requires detailed data coding and thematic analysis to uncover patterns and themes (Tracy, 2010).

The researcher endeavoured to take all necessary measures to apply and maintain the rigor and reliability of the research process, especially in ensuring data validity and reliability in this study.

3.2 Research design

The research employs a qualitative, single case study design to explore how GenAI integration impacts the roles of RMs within a leading bank in South Africa. The research design is aligned with the overarching interpretivist paradigm, emphasising in-depth understanding of participants' subjective experiences and perceptions regarding GenAI adoption (Ugwu et al., 2021).

In selecting an appropriate research strategy, several options were considered, including surveys, experiments, grounded theory, and case studies. Given the exploratory nature of this research - aimed at understanding the impact of GenAI adoption and the evolving role of RMs - a case study approach was deemed most suitable. This approach allows for an in-depth investigation of a real-world setting, providing rich contextual insights that are essential for understanding the nuanced implications of AI integration in banking (Dehalwar & Sharma, 2023).

The decision to focus on a single case, specifically one of the leading South African banks, stems from the desire to gain a comprehensive understanding of the specific organisational context, practices, and stakeholder experiences involved in GenAI adoption (Verma et al., 2024). This case provides a rich, bounded environment to explore the dynamic interactions between technology, personnel, and customer experience. While this limits generalisability, it offers detailed insights that can inform theory and practice within similar contexts.

This design enables the researcher to capture the complexity of GenAI's impact on relationship management practices and customer experience, providing contextual insights that static or quantitative methods might overlook. It also allows for the examination of organisational and individual factors influencing AI integration, aligning with the study's aims to generate actionable knowledge.

3.3 Data collection methods

The research study utilised a **qualitative design approach**, facilitated by semi-structured interviews with identified participants to effectively meet its objectives (Turner, 2010). Interviewed, were IT architects responsible for the implementation strategy of GenAI technologies within banks and, RMs who will adopt and use the technology. These 2 roles possess a wealth of knowledge and insights on the subject, and semi-structured interviews allowed for the researcher to capture their perspectives in a comprehensive and nuanced way.

The interviews were conducted virtually via Microsoft (MS) Teams, where a predetermined set of questions were asked by the interviewer. Participants were provided with the interview guide, refer Appendix A1 and Appendix A2, in advance, which allowed for adequate preparation for insights to be shared. This ensured the best possible value and outcome from the interview. The interviews were digitally recorded on MS Teams, with permission obtained from the participants.

According to Adeoye-Olatunde and Olenik, “Semi-structured interviews are the preferred data collection method when the researcher's goal is to better understand the participant's unique perspective rather than a generalised understanding of a phenomenon” (2021, p. 1360). DeJonckheere and Vaughn (2019), corroborated, suggesting that semi-structured interviews are a great method for researchers to gather qualitative, in-depth data by exploring respondent thoughts and opinions on a specific topic, particularly when delving into sensitive subjects, like GenAI adoption.

Semi-structured interviews allow for a certain degree of flexibility in the conversation, even though the researcher prepares a list of key themes. This approach can lead to changes in the order of predefined questions and allows for addressing issues raised by the interviewees that may not be included in the established themes (DiCicco-Bloom & Crabtree, 2006). In context of this research, using open-ended questions, the researcher encouraged participants to share their experiences and perspectives on how GenAI technology is impacting their work. This opened avenues for the architects, as an example, to offer their insights around the adoption challenges they have with legacy and outdated systems which positively influenced and contributed to this study’s development of knowledge in the emerging field of GenAI technology and its implications and limitations for bank lending.

The challenge with this approach, however, is that semi-structured interviews typically involve a small number of participants, and can limit the generalisability of the findings (Turner, 2010). The researcher was careful in considering the representativeness of this sample and applied due diligence to ensure the validity and reliability of the results. Interviews are also open to subjectiveness and bias (Turner, 2010) on both the parts of the interviewer and interviewee. Personal biases and preconceptions can influence the interview process and the data collected. The researcher was mindful of own biases and remained impartial and objective throughout the interview process. Interviewees can also provide inaccurate or incomplete information due to memory lapses, social desirability bias, or a lack of understanding of the research topic (DiCicco-Bloom & Crabtree, 2006). The researcher took the necessary steps to address them through probing questions and follow-up interviews. Despite these limitations, the benefits of conducting qualitative interviews outweigh the drawbacks, as they provide a comprehensive and insightful exploration of the research questions.

3.4 Population and sample

In semi-structured interviews, the population refers to all individuals who could potentially be interviewed, while the sample would be the specific individuals who are selected to participate in the interviews (Adeoye-Olatunde & Olenik, 2021).

3.4.1 Population

The unit of analysis for this study was the South African Banking industry, and participants were chosen from one of the big five banks. The ideal population group that was considered for purposes of this research were IT architects and RMs in bank lending services.

IT architects in the banking sector

IT architects are responsible for the design and implementation of secure and efficient technology solutions for all IT systems at banks. They oversee new IT projects, evaluate new and existing technologies for innovation, monitor system performance, and ensure systems meet organisational standards to maintain a reliable and secure technology infrastructure (Wessel *et al.,* 2022). In context of this research study, architects are responsible for the integration and implementation of GenAI technology in the banking sector. They possess technical knowledge and understanding of the capabilities and limitations of AI technology. Their insights can provide nuanced insights into the use of GenAI in lending services and the challenges faced during implementation. Architects' perspective on the technical aspects of the technology will aid in understanding the potential impact on RMs and customer experience.

RMs in bank lending services

RMs play a crucial role in interacting with customers and enhancing their experience (Zegullaj *et al.,* 2023). They are on the frontline of customer service and are responsible for managing relationships with clients (Colgate & Lang, 2005). By interviewing RMs who are adopting GenAI in their services, this research can understand the practical implications of using AI tools on a day-to-day basis. Their experiences and feedback provide insights into how GenAI is improving customer experience, challenges faced, and potential areas for improvement.

3.4.2 Sample and sampling method

Adeoye-Olatunde and Olenik (2021) advised that when selecting the study sample, it is important to include both individuals with in-depth knowledge on the topic and those who can offer diverse viewpoints in order to achieve a well-rounded representation. This is because sampling influences the trustworthiness of the research, depending on respondents' knowledge of the subject matter. In line with this recommendation, purposeful sampling, a widely used technique in qualitative research, was employed in this study. In purposive sampling, it is not the intention of the research to randomly sample (Bryman, 2016). Bryman posits that purposeful sampling involves selecting participants who possess specific knowledge or experiences relevant to the research topic, aiming to collect in-depth and meaningful data that directly aligns with the research objectives (2016). Adeoye-Olatunde and Olenik (2021) further recommend that the size of a sample should be determined by factors such as the research aim, homogeneity of the sample, theoretical framework, interview quality, and analytic approach.

Applying the authors' recommendations to this study, the sample was split as follows:

I. IT Architects in bank lending service: Six enterprise architects were selected based on three criteria: (1) minimum five years' experience in banking technology, (2) direct involvement in GenAI implementation projects, and (3) strategic oversight of digital transformation initiatives. To ensure effective representation for generalisability, architects were interviewed from Personal and Private Banking (PPB) and Business and Commercial Banking (BCB). The researcher also interviewed an architect that operates at bank group level for an industry wide view of the bank's GenAI strategy and adoption plan. Together, their knowledge offered a refined understanding of how GenAI is utilised in lending services and the obstacles encountered with its integration and implementation.

II. RMs in bank lending services: six (6) RMs from the same bank, spanning the different lending portfolios of enterprise, growth and premium were interviewed. The literature suggests that digitisation of the banking industry has altered the role of RMs, who must now adapt to new technologies such as automated data analysis and insight generation to better understand and meet customer needs (Miah, 2024; Zegullaj et al., 2023). They are the bank's face to the customer and are best positioned to provide a practical understanding of their experience with the adoption of GenAI tools, as well as their common experiences, challenges, and opportunities faced when using GenAI tools.

Table 3 below provides an overview of the population demographics of the architects and RMs interviewed as part of this research process. Standardly accepted in qualitative sample sizing is reaching thematic saturation, which is the point where no additional thematic information can be gathered from participants (DeJonckheere & Vaughn, 2019). In this study, reaching thematic saturation meant that once the researcher felt that sufficient information had been collected and no new themes or insights were emerging from the data, the interview process with the architects and RMs was concluded.

Code	Gender	Age	Job Level	Division	Role	Tenure (years)
P1	Male	Over 60	Consultant	PPB VAF	Enterprise Architect	Over 20
P2	Female	Over 60	Senior Manager	BCB VAF	Enterprise Architect	Over 20
P3	Male	40 – 49	Executive	BCB Technology	Head Enterprise Architect	Under 10
P4	Male	Under 40	Executive	BCB Digital	Enterprise Architect	Under 10
P5	Male	40 – 49	Consultant	Group Technology	Enterprise Architect	Under 10
P6	Male	Under 40	Middle Manager	BCB Technology	Enterprise Architect	10 – 20
P7	Female	Under 40	Middle Manager	Premium	Relationship Manager	10 – 20
P8	Male	40 – 49	Middle Manager	Premium	Relationship Manager	Over 20
P9	Male	40 – 49	Middle Manager	Growth	Relationship Manager	10 – 20
P10	Female	50 – 59	Middle Manager	Enterprise	Relationship Manager	Over 20
P11	Male	Under 40	Middle Manager	Growth	Relationship Manager	10 – 20
P12	Female	40 – 49	Middle Manager	Growth	Relationship Manager	Over 20

Table 3: Participant demographics (Atlas.ti)

Source: Author's own

3.5 The research instrument

Semi-structured interviews were used as the research instrument for purposes of this study. The researcher, with permission from the respondents, used MS teams recordings and MS Copilot generated meet minutes and transcripts, for which the researcher is licensed, to capture the data. The interviews were conducted virtually, with a set of interview questions set up in advance and presented in interview guides (Appendix A1 and Appendix A2). These were sent to participants prior the interview to allow sufficient time for adequate preparation, with the necessary insights, to extract the best possible value from the interview session.

The interview guide was deliberately structured to explore the key determinants of technology acceptance as outlined in the UTAUT2 model (Venkatesh, 2022). By examining perceptions of usefulness, ease of use, social influences and organisational support, the guide aimed to capture the multifaceted factors that influence RMs' intentions and behaviours toward adopting GenAI in banking (Dwivedi et al., 2017).

In the interview section titled "Current role that AI plays", the questions *"Can you explain your understanding of generative AI (GenAI) technology in the context of banking?"* and *"What do you believe are the main advantages of using generative AI in banking operations?*", both align to the Performance Expectancy construct of UTAUT2. The questions served to elicit from the interviewee the degree to which they believed that using GenAI could help them accomplish their work more effectively or efficiently (Venkatesh, 2022). This construct was also supported in the section titled "AI and customer experience", by the question *"How do you think integrating generative AI into relationship management practices will impact the customer experience?"*. This served to probe RMs' perceptions of how GenAI enhances the quality of customer interactions.

Similarly, the construct of Effort Expectancy was explored in the “Further Insights” section, with the question *“What training or support do you think relationship managers need to effectively integrate generative AI into their roles*?”. This question explored the perceived ease of use associated with adoption of GenAI, including training needs and ease of integration into existing workflows (Dwivedi et al., 2017).

The Social Influence construct of determining the extent to which individuals perceive that important others believe they should use the technology (Venkatesh, 2022), was addressed in the “Further insights” section with the question *"How do you think the use of generative AI in relationship management will impact customer trust and loyalty?”.* This question assessed the perception of social pressures, expectations from customers regarding GenAI adoption, and how these influence individual attitudes (Venkatesh et al., 2012).

The construct of Facilitating Conditions was targeted by asking the questions, *"What resources or support are available to help relationship managers use GenAI effectively?"* and *“Are there any organisational policies or systems that facilitate or hinder the use of GenAI in your role?"*. These questions addressed the availability of support, resources, and organisational environment conducive to GenAI implementation (Dwivedi et al., 2017).

This deliberate structuring of the interview guide ensured that the qualitative data collected effectively captured the multifaceted determinants of technology acceptance, thereby providing valuable insights into the drivers and barriers to GenAI integration within the banking context, in line with the UTAUT2 framework.

3.6 Procedure for data collection

The data collection method used for this research study was virtual MS teams interviews with the selected participants. The respondents were communicated telephonically and via email to introduce and socialise the purpose of the research study and for agreement to participate in the research. On response of agreement, participants were emailed a set of interview questions to ensure familiarity with the research ask. Appendix A1 details the questionnaire that was sent to IT architects and Appendix A2 that sent to RMs. The interview sessions were then scheduled for 30 to 45 minutes based on participant availability.

3.7 Data analysis strategies and interpretation

This research subscribed to the thematic-analysis methodology (Terry *et al*., 2017), to identify patterns and themes in qualitative data analysis. The authors, supported by Bhattacherjee (2012), advise that the researcher disclose any assumptions, bias, and subjectivity at the beginning of research, as qualitative analysis depends greatly on the researcher's analytical abilities and personal understanding of the social context within which the data is gathered.

To ensure the reliability of the thematic analysis, member checking (Turner, 2010) was employed where the researcher presented the findings back to the architects and RMs interviewed, to garner feedback on whether the themes identified accurately reflected their experiences and perspectives. This feedback was invaluable in ensuring the credibility and validity of the findings, as it allowed participants to confirm or challenge the interpretation of their responses.

Triangulation was further used to enhance the validity of the thematic analysis. Triangulation involves examining the data from multiple sources or perspectives to corroborate the findings and ensure that they are robust and reliable (Terry *et al*., 2017). In this research study, triangulation involved comparing the data collected from interviews, meeting transcripts, and AI generated notes to identify consistent patterns and themes across different data sources.

Thematic analysis, involves a six phase analytical process, as shown in Figure 11 below, which is not strictly linear, rather following a more iterative approach (Terry *et al.,* 2017).

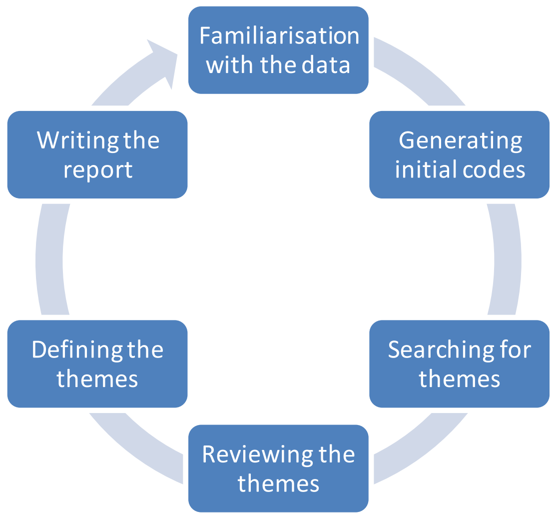

Figure 11: Thematic Analysis Process

Source: Author's own

Phase 1: Familiarisation with the data: The first step in thematic analysis involves becoming familiar with the data collected from the interviews. This includes reading through the transcripts, notes, and any other relevant materials to gain a comprehensive understanding of the data. Terry *et al.* (2017) posits that familiarisation is about a deep engagement with, and getting to know the data intimately. For this study, it meant carefully analysing the meeting transcripts, the Copilot generated meeting notes, and (re)listening to or (re)watching the audio/video recording of the interviews conducted with the architects and RMs, to pick up repetitive patterns, behaviours or experiences.

Phase 2: Generating initial codes: Once the researcher has a basic understanding of the overall dataset in the familiarisation phase, the next step involves systematically coding the data to identify key concepts, ideas, or statements related to the research questions (Braun & Clarke, 2008). This process involves breaking down the data into meaningful segments and assigning descriptive labels (codes) to them. The authors further suggest that the researcher systematically review the entire dataset, thoroughly analysing each data point and identifying recurring patterns (themes) that may emerge. Terry *et al.* (2017) acknowledged the benefits of the coding process as being flexible and iterative, meaning that the researcher can circle back through data items to clarify or modify earlier coding for consistency. The implications for this study meant looking for key concepts in the data items related to experiences and feedback of GenAI implementations and integrations, and impact to tasks performed by those using the technologies. This helped the researcher to make sense of the data, develop insights and formulate a rigorous and thorough foundation for the analysis.

Phase 3: Searching for themes: Once the initial coding is completed, the researcher then searches for patterns or themes across the coded data. This involves tying together related codes to identify main themes that capture the essence of the data (Braun & Clarke, 2008). The authors propose that this is the stage where the relationship between codes, themes, and various levels of themes becomes evident, leading to the formulation of main overarching themes and their categories.

Phase 4: Reviewing the themes: The identified themes in phase 3 are then reviewed and refined to ensure they accurately reflect the data. According to Terry *et al.* (2017), the reviewing phase is much like a quality control exercise, where the researcher verifies that the themes align effectively with the coded data, data set, and overall research objective. This may involve merging or splitting themes, as well as refining the definitions and boundaries of each theme. The authors caution against trying to get a theme to do too much as this may result in varying levels of diversity and complexity which could obscure the results. At the end of this phase, the researcher has a clear understanding of the different themes, how they are connected, and the story they tell about the data (Braun & Clarke, 2008).

Phase 5: Defining the themes: The themes identified in phase 4 are now defined and refined to ensure they accurately reflect the data (Braun & Clarke, 2008). By ‘define and refine’, the authors are referring to the essence of each individual theme, as well as the overarching theme, in order to accurately capture the specific aspects of the data that each theme represents. It is at this point that the researcher will move from a summative position - thinking about themes as lists of codes and data, to an interpretive position - telling the story that lies behind the data (Terry *et al.,* 2017). The authors stress that this phase is important in ensuring the cohesion, clarity, precision and quality of the thematic analysis being conducted.

Phase 6: Writing the report: Phase 6 begins once the researcher has established a complete set of themes and includes the final analysis and writing of the report. The researcher writes up the findings of the thematic analysis, presenting the themes along with supporting quotes and examples from the data (Braun & Clarke, 2008). The report provides a detailed account of the patterns identified within the data and their relevance to the research question.

3.8 Possible limitations and challenges of the study

Limited sample size: Since this study focuses on only one bank in South Africa, the sample size is limited, which could affect the generalisability of the findings.

Bias in participant selection: There may be a bias in selecting participants for interviews, as only those who were willing to participate were chosen, potentially skewing the results.

Time constraints: Conducting virtual interviews with architects and RMs proved to be time-consuming at times. This could result in the data collected being incomplete or the analysis rushed.

3.9 Quality Assurance

In qualitative research, ensuring rigour is essential for establishing the trustworthiness of the research findings (Lincoln & Guba, 1986). There are several strategies that can be used to determine rigour in quality assurance for qualitative research, including transferability, dependability, credibility, and confirmability (Tracy, 2010).

3.9.1 Transferability

According to Lincoln and Guba (1986), transferability refers to the degree to which the outcomes of a qualitative study can be applied to other settings or contexts. To enhance transferability, a detailed description of the research methods used, the data collection procedures, and the research participants interviewed, must be provided. This will assist readers in comprehending the context of the research and assessing how the findings may be relevant to their own circumstances.

To ensure the transferability of the findings for this study, a clear outline was provided for the specific context in which the research was conducted, the usage of GenAI in relationship management, and the characteristics of the RMs involved in the study. This was employed by means of interview guides (Appendix A1 and Appendix A2) to ensure uniformity in the data collecting procedure and allow readers to determine if the findings can be applied to other similar situations.

3.9.2 Dependability

Dependability in research refers to the consistency and reliability of the research findings and can be enhanced through transparency in the research process (Schwandt et al., 2007). To ensure the dependability of the findings, every step of the research process must be documented, including data collection methods, participant selection criteria, and data analysis procedures (Lincoln & Guba, 1986).

Section 3.8 of this study details the methods involved in ensuring dependability of findings which this research meets through adoption of a rigorous and systematic approach to data collection and analysis (Schwandt *et al.,* 2007). By conducting virtual interviews with key stakeholders, i.e., IT architects and RMs, the researcher gathered firsthand insights and perspectives on the use of GenAI in improving customer experience in banking services. This approach allowed for rich, nuanced data that strengthen the credibility and confirmability of the findings. To further enhance the dependability, this research also employed member checking as a validation technique where findings were shared with participants to ensure that their views and experiences had been accurately captured and interpreted (Lincoln & Guba, 1986). The researcher also considered engaging in peer debriefing, where feedback will be sought from colleagues or experts in the fields of GenAI and relationship management to gain different perspectives on the research process and findings (Tracy, 2010). This was, however, not followed through due to sufficient value having been gained from the interview process.

Implementation of the above strategies strengthen the dependability of this study and accurately reflect the experiences and perspectives of the participants involved. Given the dynamic nature of digital technology advancement, it is important to note that the landscape of this research will also be continuously evolving and subject to change. This may impact the ability to replicate this study in the future.

3.9.3 Credibility

Credibility in qualitative research refers to the degree to which the findings are believable and can be trusted by the readers (Schwandt *et al.,* 2007). Credibility can be enhanced through prolonged engagement with the research topic, established rapport with participants, and triangulation of data from multiple sources (Lincoln & Guba, 1986). Schwandt *et al.* proposes that thick descriptive data and direct quotes in the reporting of findings be used, to enhance transparency and allow readers to judge the credibility of the interpretations (2007). The researcher must also critically reflect on own biases and assumptions and consider alternative explanations for the findings.

In this study credibility was addressed through several aspects.

I. Conducting interviews with architects and RMs, who have direct experience with GenAI in bank lending services, afforded the researcher a method that allowed for the collection of rich and diverse data. This helped in ensuring the credibility of the findings as they are grounded in real-world experiences and perspectives.
II. Using a thematic approach to data analysis helped in establishing credibility by ensuring that the interpretation of the data is systematic and transparent. By identifying key themes and patterns in the data, the trustworthiness of findings are demonstrated to the readers.
III. The researcher used member checking to share findings with participants to confirm the accuracy and completeness of the data collected, thereby ensuring objectivity and rigour.

Overall, by following these strategies and ensuring transparency and rigour in the research process, the credibility of this study was maximised.

3.9.4 Conformability

Confirmability in qualitative research refers to the extent of which the outcomes of a study are rooted in the data collected, can be confirmed or corroborated, and is not influenced by the researchers bias or preconceived notions (Tracy, 2010). To enhance confirmability, the researcher must clearly document personal biases and assumptions, engage in reflexivity throughout the research process, and use an audit trail to document the decisions made during data analysis (Schwandt *et al.,* 2007). Additionally, colleagues or experts in the field should be consulted to review and validate the interpretations of the data (Lincoln & Guba, 1986).

Confirmability was met in this research study by ensuring that the data analysis process was transparent and that the following steps were taken to minimise the potential for researcher bias:

I. *Transparency in data collection and analysis*: This research clearly documented the data collection methods, including how the interviews with the participants were conducted and how data was analysed as specified in sections 3.4 to 3.8. This transparency allows for other researchers to follow the research process of this study and verify the accuracy of the findings.

II. *Triangulation of data sources*: This research utilised multiple sources of data to enhance the trustworthiness of the research findings i.e., interviews with RMs including their transcripts and recordings, MS Copilot generated meeting notes as specified in sections 3.4 to 3.6 of this paper, as well as document analysis and observations, documented in section 3.8. By triangulating data from different sources, the findings of this research can be cross validated to ensure their reliability.

III. *Reflexivity*: The researcher remained aware of own biases and assumptions and their potential to influence interpretation of the data throughout the research process. By being aware of own perspectives and how they may potentially steer the research, the necessary steps detailed in section 3.3 can be taken to minimise bias and enhance the objectivity of the findings.

3.10 Ethical considerations

According to Akaranga and Makau (2016), in all areas of academic writing, researchers must ensure the necessary rigour in conducting and sharing their research findings. The authors argue that because researchers are professionals, research ethics, as a subset of applied ethics, should adhere to established rules and guidelines that dictate their behaviour. Fleming and Zegwaard (2018) corroborate this, stating that research ethics requires that researchers protect the dignity of their subjects in publishing the information being researched. Herein lies the need to conduct the research exercise in a responsible and ethical manner based on grounded ethical principles.

Ethical considerations to be applied when conducting qualitative research are: anonymity, confidentiality and compliance (Gajjar, 2013).

I. *Anonymity*: Due to the nature of this study, interviews were required with IT architects and RMs employed at a leading South African bank. Anonymity is an important part of ethical research (Akaranga & Makau, 2016) and for ethical reasons, the identity of the bank, as well as the respondents, were withheld to protect the interests of the participants and the bank itself. In a digital world, where information is currency, participants were informed that their information and responses would be used solely for the purposes of the study. Furthermore, the South African POPI Act (Bruyn, 2014) protects the participants from the public misuse of their information. The selected participants were requested to partake voluntarily and their informed consent was essential. Hence, all participants completed a consent form before the researcher began the interview process.
II. *Confidentiality*: In all research procedures undertaken throughout this study, confidentiality was exercised and participants' right to privacy upheld (Fleming & Zegwaard, 2018). The researcher enforced this by withholding and masking participants' names and the bank in question. Going forward the bank will be referred to as Bank X and the participants as P1, P2, P3, etc. The original recordings and transcripts were also not submitted to protect the bank's and participants' confidentiality and privacy.
III. *Compliance*: The researcher followed the necessary governance, in applying for ethical clearance before collecting data at Bank X. Participants were also presented with the School of Business Ethics Committee clearance letter from the University of the Witwatersrand and permission from Bank X, assuring them that the proper process was followed and permission was granted, as prescribed by (Bhattacherjee, 2012). Before undertaking the interviews, the researcher provided the

participants with interview guidelines (Appendix A1 and Appendix A2), clearly detailing the full intent of the study. This allowed participants to familiarise themselves with the research and coverage in question. Participants had the right to withdraw from the research at any point in the research and were further permitted to decline to respond to any research question they could not, or did not, wish to answer. Bhattacherjee (2012) prescribes this, stating that participation in the research study is entirely voluntary and participants have the option to withdraw at any time. Additionally, all participants were treated with respect during the interview process.

Researchers have an ethical responsibility for how research data is disclosed and analysed in their research (Bhattacherjee, 2012), and this researcher remained ethical, objective and professional in abiding by the disciplines laid out above.

3.11 Conclusion of research methodology

This chapter covered the various aspects of the research methodology that were applied to this research, including the research paradigm, design, strategy, data collection, sampling methods, and participant selection. The data analysis process was explained, together with the coding approach that was used. Each method chosen was justified and connected to the existing literature, proposed framework, research questions, and research instrument. Ethical considerations were also addressed and justified using recommended principles.

The next chapter presents the research findings.

CHAPTER 4. PRESENTATION AND DISCUSSION OF FINDINGS

This chapter begins with an introduction which provides an overview of the research study, the analysis framework used, the theme development process and the code development process. This is followed by the demographics of the participants interviewed and the data analysis approach and tools used to analyse the interview data. The sections that follow are structured to present the interview findings for each research objective that was identified as part of this study, represented as themes 1, 2 and 3. The responses are analysed and discussed for meaningful insights, to assist in addressing the research objectives, in relation to the body of knowledge obtained from the literature in chapter 2.

4.1 Introduction

4.1.1 Research overview

The purpose of this study is to investigate the utilisation of GenAI technologies in enhancing the customer service offered by RMs in bank lending. Interest is informed by a critical issue in the banking industry – the need for increased efficiency, accuracy, and personalisation of services to enhance customer satisfaction and stay relevant in a very competitive financial market.

Three objectives were set for this study which the research sought to address:

1. To evaluate how GenAI transforms credit lending processes and enables product personalisation in South African banks
2. To explore how the role of the RM evolves with the adoption of GenAI and its effects on customer experience
3. To identify the opportunities and challenges of integrating GenAI into relationship management within the banking sector

4.1.2 Analysis framework

The research design applied in this study was based on the interpretivist research philosophy of an inductive nature (Ugwu *et al*., 2021). As part of the data gathering process, interviews were conducted with the 12 participants whose demographics are provided in the section below. Each participant was asked a set of questions from interview guides (Appendix A1 & Appendix A2). The questions posed were designed to take into consideration the research objectives as they relate to the UTAUT2 theoretical model (Venkatesh, 2022), presented as part of the conceptual framework in Chapter 2. UTAUT2 was proposed to be the most applicable framework in determining whether GenAI plays a mediating or moderating role on the performance expectancy, effort expectancy, social influence and facilitating conditions of RMs and customers impacted by its adoption.

The interviews were recorded on MS Teams, generating over 12 hours of interview recordings. This produced a large volume of data, which was then downloaded and validated against the recording to ensure data credibility. This meant correcting any misinterpretations and spellings whilst still ensuring the validity of the content. The cleaned data was subsequently processed using the Atlas.ti statistical software tool which assists researchers in organising, analysing, and interpreting large amounts of qualitative data such as text, audio, video, and images (Soratto, 2020). This process will be discussed in sections to follow.

4.1.3 Theme development process

Thematic analysis methodology in qualitative research entails identifying and analysing patterns or themes within data to gain a deeper understanding of the research topic (Terry *et al*., 2017). Its purpose is to uncover meaningful insights and enable researchers to draw conclusions for further research or decision-making.

The themes identified were:

Theme 1: Impact of GenAI on credit lending

Theme 2: Impact of GenAI on RM roles and,

Theme 3: Opportunities and challenges of integrating GenAI.

Each theme corresponds to a specific research objective identified in the study, providing a structured approach to understanding the underlying issues and facilitating a comprehensive analysis of the data. These are addressed in the sections below, with evidence provided by way of verbatim quotations from the interview participants. This alignment ensures that the findings are relevant and directly address the research objectives, thereby enhancing the overall validity of the study.

4.1.4 Code development and analysis

Before conducting the interviews, the researcher developed a comprehensive coding framework where the coding structure was organised around the three primary themes identified above. Each theme encapsulates various categories of meaningful insights derived from the interview questions. Within the theme *of Impact of GenAI on Credit Lending*, as an example, the categories of *Challenges, Operational Efficiencies*, and *Product Personalisation* were identified. These were then further broken down into the specific codes for each category. For the category of *Challenges*, the codes identified as challenges were *Manual processes, Data access and retrieval* and *Credit scoring.* Likewise, the codes identified for O*perational efficiencies* were, *Automation potential, Credit process optimisation* and *Risk and fraud process optimisation*.

Table 4 below provides a comprehensive overview of the themes, categories and codes that emerged from the data collected. These were further aligned to the relevant UTAUT2 influencing factors, as well as the relevant interview guide questions that support the responses.

Research Topic	Theme	Category	Code	UTAUT2	Interview Question
Generative AI's impact on bank relationship manager roles and customer lending experiences	**Theme1: Impact of GenAI on credit Lending**	Challenges	Manual processes	Performance expectancy, Effort expectancy	1.2, 3.3
			Data access & retrieval	Performance expectancy, Effort expectancy	1.2, 3.3
			Credit scoring	Performance expectancy, Effort expectancy	1.2, 3.3
		Operational Efficiencies	Automation potential	Performance expectancy	1.2, 1,3, 2.2
			Credit process optimisation	Performance expectancy	1.2, 1,3, 2.2
			Risk & fraud process optimisation	Effort expectancy	1.2, 1.3
		Product personalisation	Data-driven insights	Performance expectancy	1.2. 1.3
			Customised lending	Performance expectancy	1.2, 1.3
	Theme 2: Impact of GenAI on RM roles	Transformative potential	Evolving RM role	Social influence	2.2, 2.3
			Resistance to change	Facilitating conditions	2.3, 2.3
			Skills development	Facilitating conditions	2.3
		Impact to customer experience	Personalisation	Performance expectancy	3.1, 4.1
			Digital enablement	Performance expectancy	3.1, 4.1
			Maintaining the human touch	Performance expectancy	3.1, 4.1
	Theme 3: Opportunities & challenges of integrating GenAI	Opportunities	Improved efficiencies	Performance expectancy	1.3, 2.1, 2.4
			Personalisation	Performance expectancy	1.3, 2.1, 2.4
			Cost reduction	Performance expectancy	1.3, 2.1, 2.4
			Risk & fraud management	Performance expectancy	1.3, 2.1, 2.4
		Challenges	Data quality & biases	Perceived risk	1.3, 2.4
			Loss of human touch	Social influence	1.3. 2.4
			Job loss	Perceived risk	1.3, 2.4
			Data privacy	Perceived risk	1.3, 2.4
		Strategies for successful integration	Robust data strategy	Facilitating conditions	4.2
			Governance & regulatory framework	Facilitating conditions	4.2
			Hybrid model	Facilitating conditions	4.2
			RM Training & Support	Facilitating Conditions	4.2

Table 4: Structure of themes, categories and codes on Atlas.ti

Source: Author's own

Below is a word cloud view of the commonality of codes as they emerged in the thematic coding process on Atlas.ti. The representation clearly encompasses the key themes and focus areas of the research findings.

Figure 12: Word cloud view of coded data

Source: Generated on Atlas.ti

42 codes were created, generating 338 quotes across the 12 participants that were interviewed.

Documents	12
Codes	42
Quotations	338

Table 5: Codes generated

Source: Atlas.ti

Table 6 below, represents the document-category analysis findings from Altas.ti. In terms of participant feedback, the majority of responses (54%) came from the architects interviewed (P1 to P6), with the highest contributor being P2 (16%) and the lowest P4 (2%). In terms of feedback per category, most feedback was received for *Strategies for successful integration* (24%), whilst *Product personalis*ation had the least feedback (9%). Also noteworthy, was that 67% of the feedback received for *Strategies for successful integration* came from the architects. This validates the rationale for selecting architects as participants, as articulated in Chapter 3, given their responsibility for setting and implementing strategies for digital technology adoption within the bank.

			1: P4 6	2: P8 17	3: P3 53	4: P11 25	5: P12 23	6: P1 31	7: P7 24	8: P9 29	9: P10 27	10: P2 51	11: P5 25	12: P6 27	Totals
Challenges	6	57	2	2	7	3	7	7	4	5		7	6	7	57
Impact to Customer Experience	3	80	3	10	9	3	7	5	8	9	9	13	1	3	80
Operational Efficiencies	8	115		4	19	13	8	11	9	9	17	13	4	8	115
Opportunities	2	58	2	6	2	7	2	1	5	4	7	12	4	6	58
Product Personalisation	2	41		6	9	3	1	2	1	3	1	10	3	2	41
RM Role transformation	4	84	2	10	10	12	7	6	7	5	4	10	6	5	84
Strategies for Successful Integration	10	135	5	11	16	8	6	19	9	8	2	25	14	12	135
Totals			14	49	72	49	38	51	43	43	40	90	38	43	570

Table 6: Document-category analysis

Source: Atlas.ti

Table 7 presents a detailed exploration of the feedback received for each of the 42 codes generated from the interview data. Interestingly, *Automation potential* accounted for most responses (7%) with 61% of that feedback originating from RMs. *Customer impact* also received 7% of overall feedback with equal contributions from both the architect and RM focus groups (50% each). This trend suggests that RMs, who are grappling with the challenges of time-consuming manual processes, are likely to provide more substantial feedback regarding automation opportunities that could enhance their roles and significantly improve customer experience.

		1: P4 6	2: P8 17	3: P3 53	4: P11 25	5: P12 23	6: P1 31	7: P7 24	8: P9 29	9: P10 27	10: P2 51	11: P5 25	12: P6 27	Totals
AI Governance	21	2	2	1			2		3		5	4	2	21
Automation Potential	56		4	5	9	5	5	7	3	6	10	2		56
Biases	12			2	1						4	2	3	12
Change management	16			1	1	1	2	5	2			1	3	16
Change Resistance	16	2	1	3	1	3		2	1		1	1	1	16
Competitor Market	20		1	1	1	2			1	5	2	2	5	20
costs	9			4			1		2				2	9
costs: increase costs	2						1		1					2
costs: reduce costs	7			4					1				2	7
credit process optimisation	18			1	3	4	3		1	6				18
Customer Impact	52	3	7	6	2	3	5	4	6	4	10	1	1	52
Customer Impact: Customer Impact_Ne...	22	2	3	1		3	1	2	2	3	4		1	22
Customer Impact: Customer Impact_Po...	33	1	4	5	2	1	5	2	4	1	6	1	1	33
Customised Lending	18		4	3	2			1	2		3	2	1	18
Data credibility	14			1	2		6	1	1			2	1	14
Data Driven Insights	30		4	7	3	1	2		1	1	9	1	1	30
Data Governance measures	9						4				4	1		9
Data Security Risk	5	1		2							2			5
Digital Enablement	12		3				1			4	3		1	12
Document Processing	12		1	1	2	1			3	2	2			12
Enhanced Customer Experience	35	1	4	5	4	1	4	1	3	2	8	1	1	35
Enhanced Personalisation	19		5	1	3	1		2			5	1	1	19
Ethical AI	10			2			2				1	2	3	10
Formailsed AI Capability	11			1	1				1		4	2	2	11
Fraud Management Potential	5			3							1		1	5
Hybrid Model	15	1	2	2	1	3	1	1			1	2	1	15
Improved Efficiencies	41	2	5	1	7		1	5	3	2	10	2	3	41
Innovation	7											1	6	7
Job loss	7			1	1	2			1				2	7
Knowledge of GenAI	10			1		1	1	3	1	1		1	1	10
Knowledge of GenAI: Good knowledge	4			1			1					1	1	4
Knowledge of GenAI: Limited knowledge	6					1		3	1	1				6
Loss of Human Touch	17	1	2			7	1	3	1		1		1	17
manual process	27			1	6	2	5	4	5	3		1		27
Personalisation	34		5	5	2	4		5	3	2	6	1	1	34
Regulatory	6			1					2			2	1	6
Regulatory	6			1					2			2	1	6
Risk Management Potential	8			4		1					2		1	8
RM Evolving Role: Strategic Advisor	36		8	3	9	1	2	2	2	3	4	2		36
RM Training & Support	26	1	1	3	2	2	3	1	1		5	4	3	26
Robust Predicative Data Analytics	11						6				3		2	11
Skills Development	24	2	2	3	1		5	1			4	2	4	24
Use Cases for GenAI at the bank	30			5	3		5	2	1	7		2	5	30
Totals		19	68	91	69	50	75	57	59	53	120	47	65	773

Table 7: Document-code analysis

Source: Atlas.ti

Figure 13 presents a comparative overview of the feedback received from architects and RMs per code category. Notably, architects offered more insights regarding *Strategies for successful integration* (67%), *Product personalisation* (63%), and *Challenges associated with GenAI integration* (63%). This trend can likely be attributed to their significant thought-leadership role within the bank concerning digital technology adoption. Conversely, RMs provided a more nuanced perspective on *Impact to customer experience* (57%) and *RM role transformation* (54%), given their intimate and daily interactions with customers.

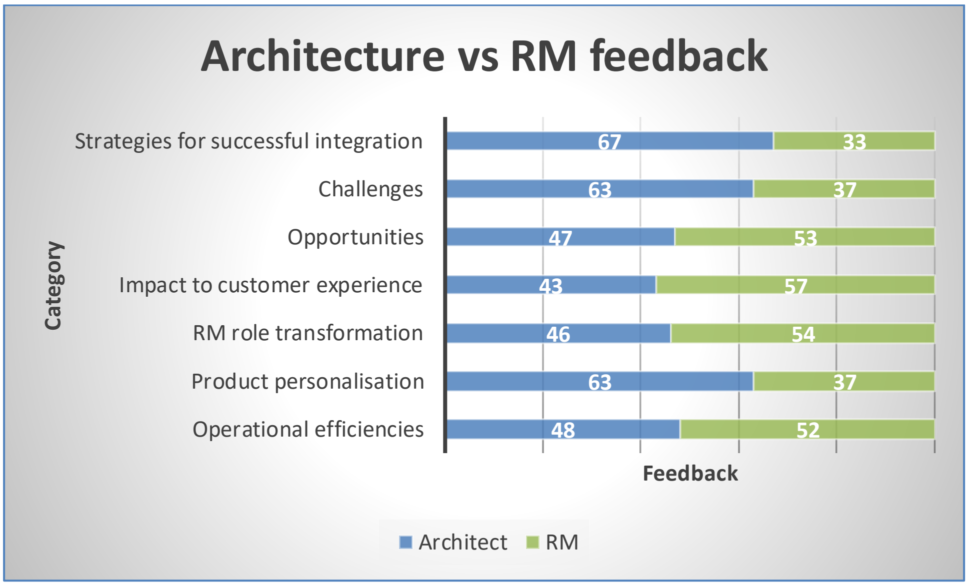

Figure 13: Architecture vs RM feedback across categories

Source: Atlas.ti

4.1.5 Participant demographics

Interviews were conducted with 12 participants from a leading bank in South Africa, comprising six (6) IT architects responsible for the implementation strategy of GenAI technologies within banks and six (6) RMs who will adopt and use the technology. In accordance with the confidentiality clause mutually agreed upon by the bank and its participants, the bank will henceforth be referred to as Bank X, and the participants will be designated as P1, P2, P3, etc.

The participant demographics are presented in Table 8 below. There were 67% males and 33% females interviewed as part of the study. The summary indicates that participants varied across age groups with most (41%) being between 40 and 49 years and the least (8%) being between 50 and 59 years. There was a mix of job levels with most (58%) being middle managers and least (16% each) being contractors and executives. In terms of job roles, there was an even distribution of 50% each between RMs and architects. Participants' tenure across the bank varied, with 33% having between 10 to 20 years' experience and 42% having over 20 years of experience.

Code	Gender	Age	Job Level	Division	Role	Tenure (years)
P1	Male	Over 60	Consultant	PPB VAF	Enterprise Architect	Over 20
P2	Female	Over 60	Senior Manager	BCB VAF	Enterprise Architect	Over 20
P3	Male	40 – 49	Executive	BCB Technology	Head Enterprise Architect	Under 10
P4	Male	Under 40	Executive	BCB Digital	Enterprise Architect	Under 10
P5	Male	40 – 49	Consultant	Group Technology	Enterprise Architect	Under 10
P6	Male	Under 40	Middle Manager	BCB Technology	Enterprise Architect	10 – 20
P7	Female	Under 40	Middle Manager	Premium	Relationship Manager	10 – 20
P8	Male	40 – 49	Middle Manager	Premium	Relationship Manager	Over 20
P9	Male	40 – 49	Middle Manager	Growth	Relationship Manager	10 – 20
P10	Female	50 – 59	Middle Manager	Enterprise	Relationship Manager	Over 20
P11	Male	Under 40	Middle Manager	Growth	Relationship Manager	10 – 20
P12	Female	40 – 49	Middle Manager	Growth	Relationship Manager	Over 20

Table 8: Participant Demographics (Atlas.ti)
Source: Author's own

Although the sample size of 12 participants may be considered small, Dworkin (2012), in addressing the challenges associated with small samples in qualitative research, notes that the primary limitation is saturation, which refers to the point at which no new themes, ideas, or insights are emerging from the data, and restricts the variety of responses obtained from interviewees. To mitigate this, the sample has been controlled and the questions designed to reduce the risk of saturation. Participants have also carefully been selected to ensure a range of experiences, skillsets and perspectives.

4.2 Theme 1: Impact of GenAI on credit lending

This theme sought to assess how, through automation and adoption of GenAI technologies, banks could transform their credit lending processes and personalised product offerings for improved operational efficiencies and enhanced customer experience. The following categories were identified in the interview process: Operational efficiencies and Product personalisation. Before delving into the opportunities for operational efficiencies and personalisation, it is worthy to first understand the current challenges that RMs face on a day-to-day basis.

4.2.1 Challenges

Participant interviews revealed several significant challenges faced by RMs in bank lending, such as administratively demanding tasks, manual data entry and cumbersome onboarding processes. This is exacerbated through inefficient data access and retrieval processes and well as the sub-optimal credit lending processes currently implemented at Bank X.

4.2.1.1 Manual processes

In this section, participants belaboured the extensive amount of time spent on manually preparing documentation, a key challenge and barrier to effective credit lending. P1, P2, P8 and P11 all highlighted the tedious steps involved which rely heavily on individual RM effort.

> *“The RM spends a lot of time doing relatively low value simple work, information gathering, summarising things.”* ***- P1***

> *“We do pretty much everything that I can think of in a manual process. There's a whole lot of documents that are not even prepopulated for the client.”* ***- P8***

> “*Nothing is automated to any degree. One mandate manually takes probably takes 2 to 3 three hours out of your day.”* ***- P11***

P7 stated that manually inputting financials such as balance sheets and income statements into systems is a lengthy process and prone to human error. Both P11 and P12 lamented that opening new accounts requires extensive documentation and is a labour-intensive and time-consuming process which takes several hours. The acquiring of electronic or physical signatures for mandates is often an elaborate, cumbersome process that hinders efficiency.

> *“Sometimes our work requires so much paperwork and it's just cumbersome to be honest, like opening an account. If you need documents upon documents to open an account, sometimes it's just hurdles along the way.”* ***- P12***

P5 and P7 further added that the credit application process for onboarding a client was labour-intensive and could take anything up to 2 days to finalise with the risk of loss of customers to competitors. P1 concurred, adding that the process for evaluating credit risk was still heavily reliant on manual checks and valuations.

> *“Onboarding a client is a lengthy process, followed by logging of calls…losing a lot of business to competitors.”* ***- P5***

> *“I mean a credit application depending on the complexity of it, can take me two days sometimes because there's so much information to input.”* **- P7**

P10 mentioned ongoing Anti-Money Laundering (AML) checks and validations which necessitate more manual review and document handling thus impacting RM ability to focus on sales - the bread and butter of any business.

“So we definitely need a better process there because we're finding if they're doing AML, there's no sales.” ***- P10***

In addition to the challenges associated with the lending process outlined above, P10 further highlighted the cumbersome way in which meetings are currently minuted and the feedback distributed. This manual approach can take several days to finalise and distribute, resulting in delayed feedback.

“About 3 days later, the PA is sending out the minutes of the meeting, which is a couple of pages long, and the poor lady is actually physically typing out all that.” **- P10**

Participant feedback aligns with the literature findings of Zegullaj *et al*. (2023) presented in Chapter 3, who claimed that manual procedures and outdated systems frequently hinder RM ability to provide efficient customer service, resulting in prolonged processing times and lower customer satisfaction levels. Similarly, Ionascu and Barbu (2023) observed that advisors spent considerable time manually processing and analysing customer data, relying on traditional spreadsheets.

4.2.1.2 Data Access and Retrieval

Responses indicated that the bank’s systems are complex in nature and difficult to navigate, resulting in failure to utilise available data effectively. According to P12, this hinders quick access to relevant client or financial data leads and subsequently delays decision-making. P1 added that analysing and interpreting large amounts of data from various sources is still largely manual, requiring intensive effort for proper scoring and validation.

“Sometimes I feel like the information we looking for or we want is not readily available. I think, sometimes our systems are also a little bit complex where you don't actually know where to look for something.” - ***P12***

The above feedback is supported in the literature, with Palaparthy and Pillalamarri (2015) recognising the lengthy manual processes and documentation in the existing credit processes. Ionascu and Barbu (2023), further noted the considerable time that RMs spent in manually processing and analysing customer data, often using traditional spreadsheets.

4.2.1.3 Credit Scoring

Feedback surfaced several recurring themes that highlight the challenges faced in credit lending divisions of banks. These include ineffective credit scoring and fraud and risk management inefficiencies. P11 indicated challenges dealing with fraud queries which presently requires the RM to facilitate the entire process manually on behalf of the customer.

> *"Fraud is becoming increasingly problematic, consuming significant time. Customers receiving SMS alerts for fraudulent transactions encounter challenges in reporting incidents, relying on RMs to initiate fraud cases and provide reference numbers."* ***- P11***

Respondents further noted inefficiencies in fraud checking and validation processes, with P2 raising the risk of inaccurate credit scoring due customers sometimes submitting falsified documents to positively influence their credit rating.

> *"Risk of defraud with respect to credit and lending … sometimes people submit fraudulent documents."* ***- P2***

The findings align with the literature of Sadok *et al*. (2021), who suggested that traditional time-consuming processes, and the subjectivity that arise, can cause RMs to make mistakes and introduce bias into decision-making. This can result in inconsistent outcomes compounded by the reliance on limited data sources. In the discussion with interviewees, it emerged that automation of manual processes could aid in addressing the operational inefficiencies that RMs experience. This will be discussed further in the next chapter.

4.2.2 Operational Efficiencies

In this section, respondents identified various opportunities for improving Bank X's lending operational efficiency through automation and credit process optimisation.

4.2.2.1 Automation potential

Participants noted that automation through AI and digital tools could significantly reduce time spent on administrative tasks. P3 indicated that AI tools could automate repetitive tasks to reduce time.

> *"It's more around automating of repetitive tasks so they can save time and reduce the time spent on workloads that are repetitive and mundane, and this can lead to an increase in productivity and decisions."* ***- P3***

> P1 suggested that the use of MS CoPilot to automate minute taking and reduce the workload on RMs could be the most significant operational efficiency in banking at present.

> "*CoPilot can improve operational efficiency … take away the lengthy process of transcribing and turning into minutes … integrating GenAI with processes and workflow I think is probably going to be the biggest operational improvement in the bank actually for quite a while.*" ***- P1***

P5 supported this view, stating that the anxiety of starting an email or document from scratch on a blank page is often underestimated. AI content generation can quickly transform points into polished documents, allowing RMs to focus on the actual content, instead of worrying about syntax and formatting.

> *"What should probably not be underestimated … is taking away the anxiety of a white page of starting an e-mail or starting a document. Content generation can really help an RM go from one or two bulleted points to a very polished document in a very quick space of time. So they actually think about the tough stuff rather than have they got the syntax right?"* ***- P5***

P1 also proposed that leveraging AI to automate manual data gathering processes required for financial assessments and credit evaluations could lead to streamlined operations. This would ultimately improve operational efficiency.

> *"The automation of, and support of processes that the RMS are doing … quite a lot of research particularly in private banking and in commercial banking … information gathering and trying to summarise things, and GenAI is quite good at that."* ***- P1***

Additional feedback was that integrating AI solutions would save time spent on tedious administrative tasks and reduce pressure on RMs, thus enabling them to focus on strategic and meaningful client interactions and decision making. P11 added that leveraging AI technologies for analysing customer data would greatly aid in improving customer service and efficiency within the bank.

> *"I could leverage AI assist me with a lot of the hard analysis …give me the standout points rather that allows me to make a more quicker and informed decision for our clients ... our response to the clients would be a lot quicker and efficient."* ***- P11***

The overall feedback from participants was that leveraging GenAI technologies can significantly enhance operational efficiency, streamline processes and improve customer service, thereby driving productivity within the bank. This sentiment is reinforced in the literature by Krijger (2023), who similarly recognised the recent surge in GenAI adoption in banking, driven by opportunities for improved customer experience, streamlined operations, reduced costs and more informed decision making. Kalia (2023) corroborated, stating that the banking industry has entered a new era, one that will be propelled by GenAI for enhanced automation and innovation. Domokos and Sajtos (2024) reinforced this, stating that digital transformation is set to enhance customer experience and drive significant revenue growth, well positioning banks to thrive in competitive markets.

4.2.2.2 Credit process optimisation

Feedback from participants suggest that the optimisation of credit processes in bank lending should focus on enhancing credit scoring, as well as risk and fraud management, using data analytics and technology integration.

Credit Scoring

Participants P2 and P3 suggested that by utilising GenAI's advanced data analytics capabilities to analyse large datasets like financial statements, cash flows and market trends, banks can significantly improve the accuracy of credit scoring and decision making.

> *"Its ability to analyse vast amount of data would make it more accurate for credit scoring and risk management." **- P3***

> *"Improve credit risk and operational risk appetite by using predictive insights to make better informed decisions." **- P2***

The responses above are supported in the literature by Kayode (2024) who recognised the ability for ML algorithms to automate the credit process by analysing vast amounts of data to determine creditworthiness. Bhatore *et al*. (2020) suggested that GenAI can eliminate bias and subjectivity from the decision-making process by relying on data-driven insights instead of human judgment. This is professed to eliminate manual reviews, facilitating quicker credit approvals. Interestingly though, the architects interviewed argued that automation could in fact do just the opposite - introduce algorithmic bias into the credit decisioning process. Whilst existing literature does recognise issues of algorithmic biases in GenAI, the nuanced ways in which these could manifest or influence existing RM decision making practices requires deeper analysis. This will be further explored in Chapter 5.

Loan processing

Participants responded that GenAI could streamline the lending application process by providing customers with personalised pre-qualification options. It could guide customers through the necessary documentation and requirements, making the process smoother and more accessible. P3 noted the potential for loan performance monitoring to proactively identify issues related to timeous payments.

> *"… loan monitoring and management…provide early warning signs of potential issues such as late payments or financial distress."* ***- P3***

This approach could help raise awareness and mitigate the risk of loans going into financial distress. P1 added that GenAI has the ability to effectively process large datasets from various sources, including transaction histories, credit reports and external economic indicators. It can thus identify patterns and anomalies in borrower behaviour, that may not have been immediately apparent to the RM, through the use of sophisticated algorithms. As an example, if a borrower shows a gradual increase in late payments or a consistent decline in their cash flow, GenAI could flag this trend early, allowing RMs to take proactive measures.

P8 illustrated the opportunity for GenAI to analyse relevant data points directly linked to banking systems, such as Home Affairs data, and streamline the information-gathering process to minimise client frustration.

> *"Read Home Affairs data…extract the data instead of asking the client and frustrating them for things."* ***- P8***

P11 indicated that banks could use GenAI's ability to analyse financial statements to provide deep and meaningful insights to credit bureaus for enhanced credit scoring and decision making.

> *"The ability take financial statements from the clients ... deep analysis on our clients' industry … it would be very awesome if we could have a system analyse*

> *… we want to see what we could offer to the client … make an informed decision and have our credit team align to that as well." -* ***P11***

P11 further added that GenAI could assist less experienced staff prepare comprehensive credit papers by identifying missing information, thus enhancing overall understanding of client profiles and bridging knowledge gaps across teams. He substantiated, sharing that his many years of experience at the bank has given him a good understanding of how to position a credit paper, however RMs that start new to the bank, possibly graduates, struggle to articulate the client holistically. The view is that AI could solve for this, where the RM could potentially run the paper by GenAI and pick up any gaps in the client history, which could be remediated.

> *"I have done hundreds of credit papers over the years … have a very good understanding of how to position or prepare a credit paper for our credit team …what I do find internally and I suppose it's a knowledge thing … colleagues starting within the bank fairly young struggle to put that type of paper together ... articulate that client holistically to our credit team … GenAI could bridge that gap … help you correct that paper … it could be a nice link."* ***- P11.***

The feedback above is corroborated by Adamek and Solarz (2023) who stated that the decision-making process can be enhanced by GenAI to evaluate creditworthiness and improve accuracy in loan approval through the analysis of data points in the process. Oracle (2021) concurred, stating that GenAI could mitigate biased rejection rates and allow for fair decision-making.

4.2.2.3 Risk and fraud process optimisation

Participants responded that GenAI has the potential to augment traditional risk and fraud management processes in bank lending for enhanced decision making and customer credit insights. P2 and P4 mentioned the ability to factor in non-traditional data points like cash flow trends and spending patterns, commonly overlooked by standard models. This could open up lending opportunities to customers who would otherwise have been classified as high-risk based solely on traditional criteria.

P3 suggested that GenAI be trained to recognise patterns and anomalies that indicate fraudulent activity. By analysing large datasets of transaction records, customer behaviours, and historical fraud cases, GenAI algorithms can identify unusual patterns real-time, flagging potential fraudulent transactions or behaviours. P3 further noted that GenAI can create more nuanced profiles of customers by evaluating financial behaviour over and above past credit history.

> *"I think the biggest being that it can enhance credit scoring and risk and fraud assessment. Its ability to analyse vast amount of data would make it more accurate for credit scoring and risk assessment."* ***- P3***

P2 concurred, noting GenAI's ability to analyse historical borrowing and repayment data which would allow for the predictive likelihood of default or risk levels associated with certain customers. This would help the bank make informed decisions on who to lend to and, under what terms.

> *"We use AI in modelling credit risk and operational risk by generating predictive insights, which is helping the bank to make better informed decisions to minimise the risk."* ***- P2***

P1 additionally suggested that GenAI could efficiently analyse loan applications and supporting documents, extract relevant information, cross-reference data points, and identify inconsistencies that may indicate fraudulent intent.

> *"We can also use it in in loan application processing for risk assessment and fraud detection. By analysing vast amounts of data, to identify patterns and anomalies which can be an indication of fraudulent activities. So this would help with any detection and prevention of fraud."* ***- P1***

The findings are supported in the literature, with Kalia (2023) observing that the analysis of big data, credit history, etc., enables ML models to optimise the loan approval process and create more accurate credit risk profiles. Accenture (Abbott, 2024) further recognised the ability of ML and NLP to transform how banks analyse customer data, recognise patterns and make data-driven decisions. The literature has shown that by utilising these technologies, RMs can gain a deeper understanding of customer preferences, behaviours and credit risk profiles, allowing them to tailor lending products and services to meet individual customer needs (Sharma *et al*., 2023).

4.2.3 Product Personalisation

Product personalisation in bank lending entails the tailoring of specific lending products or services using data-driven insights and customised lending requirements to better serve the bank's customers. Its effectiveness, though, is heavily dependent on high-quality data and strong data integration frameworks. Feedback from participants is that leveraging data-driven insights and customised lending through GenAI not only offers personalised lending opportunities but also improves customer experience and operational efficiency in the lending process.

4.2.3.1 Data-driven insights

Data-driven insights refer to the use of advanced analytics and machine learning models to extract actionable information from large amounts of customer data (Devan *et al*., 2024). This includes behavioural patterns, credit histories, and market trends that influence lending. Responses suggest that these insights could inform decision-making for tailored lending solutions to customers. P1 observed, however, that its effectiveness is heavily dependent on high-quality data and strong data integration and governance frameworks.

> *"It's all about the data integration, the data quality, validation and preparation and about the data governance behind."* ***- P1***

P10 mentioned that the Bank X has provided some form of data aggregation enablement through implementation of tools like Bizflex, Smart2 and Proact for RMs to have better customer insights. These tools aggregate comprehensive customer data and present consolidated views which RMs can easily access and leverage for a single view of their customers portfolios. P11 argued, however, that although Smart2 generates insightful customer data, it is not a predictive analytics tool and therefore cannot provide the deep analysis required to recommend customised lending solutions to customers. RMs still do this manually by analysing the data themselves.

> *"Smart2 has insights on our clients' industry, deposits, credits, ratings. It would be very awesome if we could have a system dissect all of it and look at some of the main drivers over the last few years of the business, what we could offer to the client. A lot of that deep analysis that we do currently very manually could be done by the system that will allow us to make an informed decision."* ***- P11***

P8 elaborated that GenAI could empower customers by providing them with data insights, thereby enhancing their ability to initiate engagement. He indicated that clients who were equipped with insights regarding their portfolios, and what they qualify for, could now proactively approach RMs to enquire about prescribed offerings. This would reduce the effort needed for RMs to initiate product discussions and make for more empowering conversations for the customer.

> *"If the data is continuously being available to clients … your client is then proactive saying, apparently, I qualify for R2m in terms of asset financing … So, I'm not building up a conversation on how do I sell him R2m? He already knows he qualifies for it … it takes that out of the conversation and makes it easier to sell to the client."* ***- P8***

P3 further mentioned predictive analytic opportunities for proactive detection of fraud and security issues before they actually occur. This could then be provided back to the customer as an added service, aiding in strengthening customer trust and showcasing the bank's commitment to protecting their assets.

"The proactive engagement, we are actually going to be detecting fraud and security issues before they happen. The customers would love this very much because we would be helping them to protect their accounts, and this builds trust with the bank's ability to safeguard their assets." **- P3**

The feedback above is supported in the literature by Donepudi (2017) who noted the ability for AI software to analyse and identify patterns in historical data to make predictions. Singh and Singh (2024) corroborated this, highlighting the potential for GenAI to provide tailored recommendations and advice based on customers individual needs, thereby serving to enhance the overall customer experience. Kayode (2024) and Kalia (2023) agreed, emphasising the capability of big data and predictive analytics to determine creditworthiness, generate accurate credit risk profiles and optimise the credit approval process.

4.2.3.2 Customised lending

Customised lending refers to the practice of tailoring loan products and terms to meet the specific needs and preferences of individual customers (Akhileshwari, 2023). By leveraging predictive analytics, GenAI can identify the most suitable lending products for each customer based on their financial behaviour, needs and goals. P5 suggested the ability for GenAI to continuously analyse real-time data, presenting the opportunity for alerting RMs about key events in a customer's financial life such as upcoming large expenses or changes in income. This would allow for RMs to reach out proactively to suggest relevant lending options before the client even identified the need. This could potentially improve the likelihood of loan acceptance and repayment.

P11 added the ability for RMs to use tools such as Smart2 to identify opportunities for cross selling of products and services by leveraging access to detailed customer data. This could ultimately drive revenue growth within their portfolios.

"Previously you'd have to go into the customer bank statement, interrogate what transactions are going off his account, trying build or paint a picture of the client.

Smart2 now obviously pulls all the data from every other system. If we could cross sell that kind of data, will help you to increase the revenue within your portfolio." ***- P11***

P11 further acknowledged the opportunity for GenAI to provide accurate, personalised banking services tailored to customers' individual needs, stating that sometimes customers are prescribed incorrect product offerings by RMs when not all the data is available to provide an informed view. He quantified that the consequence of incorrectly prescribing a product without fully understanding the customer's business could both disadvantage the customer and negatively impact the bank.

"I think a lot of missed opportunities with clients is where they are certainly not aware of a lot of the lending products that we do and what they may qualify for. That could be a main driver, in my opinion, in implementing GenAI in lending. Sometimes we perhaps give the wrong product, and it ends up hurting the business a little bit more. Whereas something like GenAI would be very trained from a knowledge perspective probably even more so you …we would oversee that process and really be able to get that to the client." ***- P11***

Both P2 and P9 surfaced the importance of understanding customer specific needs and that optimal timing for product offerings is critical. P2 suggested advanced analytics as being beneficial in predicting customer requirements based on historical behaviours. P11 alluded to seasonal trends dictating the timing of prescribed offerings to clients, thus enhancing customised lending services.

"There also comes to mind predictive analytics … by analysing the data on the customer behavior, the payment history … where there could be a future trend for customer needs that also could help relationship managers to proactively offer products that is appropriate at the right time for the right person, for the right reason. It also helps them to make real time decisions with real time insight." **- P2**

> *"Timing is such a critical part for our clients. To understand when to offer a certain product and just not offering it for the requirement its flagged for. Is this a seasonal business? Are they looking for certain requirements and then already pre-empt that to me or to the client directly."* ***- P9***

The feedback above is supported in the literature by Donepudi (2017), who mentioned the ability for AI software to analyse and identify patterns in historical data to make predictions. Singh and Singh (2024) corroborated, highlighting the potential for GenAI to provide tailored recommendations and advice based on customers individual needs, thereby serving to enhance the overall customer experience. Kayode (2024) and Kalia (2023) concurred, emphasising the capabilities of big data and predictive analytics to determine creditworthiness, generate accurate credit risk profiles and optimise the credit approval process. Bhatore *et al*. (2020) further proposed data-driven insights to remove bias and subjectivity from decision-making.

4.2.4 Alignment to theoretical framework

In this section, participants highlighted the current challenges of excessive time spent by RMs on low-value, menial tasks which greatly hinder their ability to provide optimal service to clients. This includes manual processes, data access and retrieval challenges and inefficient credit processes. Participants suggested that operational efficiencies and product personalisation could alleviate these challenges. Faster service delivery through automated workflows would result in improved turnaround times and customer satisfaction, which is crucial in a competitive banking landscape where clients expect timeous responses.

Literature and interview findings also suggest that GenAI automation could eliminate bias and subjectivity from the decision-making process through data-driven insights rather than human judgment. The findings of Bhatore *et al*. (2020) supports this view, with the authors proposing data-driven insights to remove bias and subjectivity from decision-making. This was counter-argued by some architects who had the opposing view that GenAI could actually inherit and exacerbate existing RM biases in the manual credit decisioning process due to preferential customer demographics. This requires deeper analysis and resolution.

UTAUT2 alignment

It can be deduced from the discussion that the impact of GenAI on credit lending aligns closely with several constructs laid out in the UTAUT2 framework.

Performance expectancy: This construct relates to how much individuals believe that utilising a technology will improve their work performance (Venkatesh, 2022). Feedback from participants indicated that GenAI can significantly enhance operational efficiency, credit scoring accuracy, risk management, and customer service. This is in alignment with the construct which suggests that users are more inclined to embrace a technology if they perceive it will enhance their performance results. For instance, the ability to automate repetitive tasks, streamline processes, and improve the accuracy of credit assessments are clear performance benefits highlighted by respondents. The findings are corroborated by Sharma *et al*. (2023), who indicated that adopting GenAI could enhance credit lending procedures and shorten processing times by automating the collection, verification, and underwriting of documents.

Effort expectancy: This construct pertains to the perceived ease of use associated with the use of a technology (Dwivedi *et al*., 2017). Participants expressed that GenAI could simplify and reduce the time needed for administrative tasks, thus enhancing usability for RMs. P3 and P1 cited GenAI's ability to handle mundane tasks and provide quick insights as enablers to reducing effort required from RMs. This aligns with the construct, where the perceived ease of use of a technology influences its adoption. The observations above are supported in the literature, with Tad *et al*. (2023) also noting that AI and ML technologies could address the challenges of manual and lengthy processes.

Social influence: This construct pertains to how much individuals recognise the importance of other's expectations concerning their adoption of the new technology (Venkatesh, 2022). Endorsements from RMs, highlighting positive experiences and efficiencies gained through the adoption of GenAI, could effectively promote its acceptance in other roles and departments across the bank.

Facilitating conditions: This construct refers to the resources and support available to engage with the technology (Venkatesh, 2022). Feedback hinges on the need for strong data integration frameworks and high-quality data to maximise GenAI's benefits. P1 noted that effective data governance is crucial for leveraging data-driven insights. The feedback above is supported in the literature by Adamek and Solarz (2023), who noted that GenAI can improve the accuracy of the credit lending decision-making process through analysis of the various data points in the process. Kayode (2024) and Kalia (2023) further proposed the use of big data and predictive analytics to assess creditworthiness, create more precise credit risk profiles, and improve the loan approval process. The ability to implement AI effectively depends on the infrastructure, support and resources that an organisation provides, which is an essential consideration for the successful adoption of any technology.

Price value: This construct refers to the perceived balance between the cost of adopting a new technology and the perceived benefit of value that the technology will provide to the user. While not explicitly discussed, the idea that improved efficiency and accuracy could lead to lower costs and higher revenues suggest an appealing price-value perception of adopting GenAI technologies. JPMorgan Chase's adoption of COIN supports this theory (Weiss, 2017). COIN (Contract Intelligence), a digital solution, was utilised to automate loan agreements, enabling the bank to process loans in just seconds. This innovation saved the legal department 360,000 hours in processing time, improved efficiency and ultimately lowered operating costs.

4.3 Theme 2: Impact of GenAI on RM roles

Theme 2 of this study sought to assess how, through adoption of GenAI technologies, the role of RMs could be transformed from transaction processors to trusted advisors, ultimately enhancing customer experience. The following categories were identified in the participant interviews: Transformative potential and Impact to customer experience.

4.3.1 Transformative potential

Feedback from participants indicate that the adoption of GenAI tools to automate manual and routine tasks will allow the role of the RM to transform from information gatherers and document processers to that of customer-centric advisor. While certain participants felt that RMs would be enthusiastic about embracing this change, others believed that there may be resistance due to concerns about job security. Participants further recognised the need for development of new skills to learn how to use AI prompting for effective outcomes.

4.3.1.1 Evolving RM role

Responses acknowledged that GenAI adoption would result in data automation, aggregation and personalisation efficiencies. RMs are expected to transition from primarily data gathering and processing to a more strategic role of providing personalised and tailored advice to customers.

P2 highlighted the opportunity for RMs to shift focus towards building trust and fostering personalised relationships with clients, leveraging the data insights offered by AI. This will enable them pivot from the manual, labour-intensive tasks they once handled - now a potential for AI automation and focus instead on more strategic relationship building with customers.

> *"GenAI can take over more administrative and routine tasks, so relationship managers must likely shift more towards the strategic functions… will need to enhance their soft skills … empathy, building trust and connection."* ***- P2***

P9 echoed this sentiment, noting that the current time spent by RMs on manual processes and support roles acts as a barrier to delivering value-added services to business.

> *"It makes it such an important point there where it takes from our time … like for me the support role is difficult and I would think AI would really help … frees our time to actually do more valuable sort of requirements for the business."* ***- P9***

This was further supported by P7 who added that clients would now benefit from RMs having relevant insights readily available, which could lead to more informed discussions and potentially higher revenue generation through product personalisation and customised lending offerings to customers.

> *"I think would be it would create more efficiency. It will help us to get things done quicker. Our turnaround time to our clients will be quicker. We can give more succinct answers to them because we've got data that is so accurate. And obviously spending more time with them as well."* ***- P7***

The feedback above is in line with the findings of Adamek and Solarz (2023) who recognised that, as banks increasingly adopt technology to automate processes, RMs are required to shift in their roles to improve customer experience. Sharma *et al*. (2023) concurred that this shift towards digital solutions, not only transforms the way RMs engage with customers, but also significantly enhances the overall lending experience for clients. Singh (2024) concluded that banks will undergo fundamental changes as skilled individuals globally leverage GenAI technologies for problem-solving and innovation.

4.3.1.2 Resistance to change

Whilst GenAI adoption is believed to transform and enhance the RM role, participants also acknowledged the potential negative impact it could have with the perceived threat of job losses. P3 and P11 expressed concerns that RMs may view technology automation as a threat to their jobs, which could lead to resistance to adoption.

> *"AI can also lead to job displacement. The mundane tasks were actually being done by individuals. So, what we might see is in time certain jobs being taken over by AI and those jobs become redundant and those people ending up out of the job."* **- P3**

> *"It will ultimately take away a lot of roles in the future."* ***- P11***

P5 and P6 had an alternate view, suggesting that a digitally transforming workforce will naturally filter out individuals who do not take the opportunity to upskill themselves.

> *"I think we're going to have an evolving workforce … I don't think AI is going to replace people's roles. What I think will happen is they'll get superseded by people that are using AI in their roles. And so, I think that's going to be an evolution in the workforce."* ***- P5***

> *"AI is not gonna take over people's jobs. People who know how to use AI will."* - ***P6***

P3 and P7, however, believed that AI is not meant to replace people's roles but rather to enhance them.

> *"I don't think in business banking you can ever replace the RM. So, AI will only be a support that would actually enhance their job."* ***- P3***

> *I think they will adapt quite easily because I've seen it happen many times. They will be open to whatever kind of process can help them to be more*

*efficient … not necessarily saying so that we can do less work. The point is just to be more efficient." **- P7***

P8 and P11 concurred, stating that the shift will result in a workforce where those who effectively utilise AI will excel, therefore, key focus should be on enabling staff adoption. P3 added that organisations need to be prescriptive in how they train employees to gain collaborative buy-in.

*"Rather learn how to use AI tools to your advantage I think to better serve your day, you know, and make sure you get into all the things as quick as possible." **- P11***

*"It also requires that we change the way we manage employees to ensure that they are adequately trained. Sometimes technology frustrates, so there would actually need to be careful consideration of how we apply it and where we apply it." **- P3***

P7 felt that resistance to change could also be expected from older, non-tech savvy staff who would struggle to adapt.

"Maybe the older guys won't take to AI as much as the younger guys will. So maybe a slow integration of it, you know, piece by piece." **- P7**

P5 refuted this, arguing that age is not the determining factor, as older employees have shown the ability to quickly adopt new technologies, adding that the key lies in willingness and motivation to learn and utilise these tools effectively.

*"It's not an age thing I've seen very senior people pick this up really quickly. I think it's the level of enablement. If you feel you are self-motivated and self-driven, you'll pick this up, you will do so." **- P5***

Overall feedback was that, while GenAI offers RMs a chance to redefine their roles and leverage technology to provide more personalised and informed client engagements, there is the risk of resistance to adoption. This is due to facilitating factors such as the perceived threat of job loss or lack of technical knowhow.

While existing literature supports the feedback above, with Ooi *et al*. (2023) acknowledging that integrating GenAI technologies into the workplace may lead to resistance, it does, however, lack understanding of why RMs are actually resistant to change and there is a foundational lack of knowledge on the root cause of resistance to GenAI adoption. Feedback from RMs interviewed in this study has clarified that while some may view technology automation as a threat to their jobs, others really have limited or no GenAI knowledge altogether. This could be a key determinant in the resistance to adoption. The research addresses this shortcoming in the next section and provides interventions in Chapter 5.

4.3.1.3 Skills development

Participants acknowledged that successful adoption and integration of GenAI will require RMs to be equipped with specific skills. Two levels of training are needed for RMs to adapt to their evolving roles: one focusing on soft skills for enhanced customer engagement, and the other centred on the effective use of AI technologies for ease of use.

P2 indicated that RMs should enhance their empathy, communication and collaboration skills when having one-on-one engagement with customers. P3 alluded to skills development to leverage GenAI in supporting them in their existing roles.

> *"There's an emphasis almost on soft skills because AI will handle all the data-driven tasks, so the relationship managers will need to enhance face to face empathy, communication building."* ***- P2***

> *"The kind of training they might need is how to leverage AI to best support them in their job, to actually be able to augment them, because that human interaction is still necessary in our space."* ***- P3***

The second level of training would entail upskilling, focusing on AI literacy, ethical handling of AI-generated data and best practices for customer engagement. P11 recommended basic AI training for individuals with limited knowledge to enhance their understanding of fundamental concepts, thus enabling them to effectively leverage AI.

> *"Once people understand how the core basics of an AI model works, how that could help them on their day-to-day basis … use it to your best ability to get the most out of that system."*- ***P11***

P2 and P7 suggested training on integration and use of GenAI tools, specifically on how to apply proper prompt engineering to gain the right level of insights, to reduce false output and hallucination and avoid biases.

> *"How to do the right prompting … understand how to integrate data to these systems, to interpret them and how to get the right outcomes. I think a very big training is the ethical and compliance training, focusing on avoiding bias."* ***- P2***

> *"They will need to learn how to effectively collaborate with AI systems to do the right prompting."* ***- P7***

P6 shared his personal experience of undergoing prompt engineering training, which he credited to the effective adoption and utilisation of GenAI in his role.

> *"One of the biggest things that I did that I think enhanced the way I looked at AI was taking a course on prompt engineering. And I felt like doing that allowed me to utilise AI to a better potential."* ***- P6***

P5 added that Bank X is already seeing a reduction in hallucinations from 10% to 1% by implementing effective prompt engineering techniques. However, this reduction is still not optimal and the bank aims to achieve a rate of less than 0.01% to meet the stringent tolerance levels required in the highly regulated banking industry.

> *"Let's just say that it was maybe one in 10 that was hallucination. Now we're getting it down to one in 100. Unfortunately, when you operationalise in the bank, it's got to be down to one in a few thousand before you get those tolerance levels up."* ***- P5***

Overall, feedback from participants suggest that a balanced development of interpersonal and technical skills is essential for RMs to succeed in an evolving landscape and stay relevant in a competitive market. Accenture (2024) addressed this issue at industry level, emphasising that the banking sector must develop new skills, adopt innovative approaches, and foster new mindsets at all organisational levels in order to remain relevant in a digitally transforming environment. The feedback is supported, with the findings of Miah (2024) proposing that employees would need data analytics training as well as interpersonal skills training to gain credibility and trust with customers. The literature is limited, however, in knowledge of how RMs specifically, would need to refine their skills to best leverage the use of GenAI in a very complex credit lending landscape. Feedback from the interviews conducted suggest the need for RMs to be trained on prompt engineering to reduce hallucination, errors in output and biases. Chapter 5 addresses the approach.

4.3.2 Impact to customer experience

Participants were asked to share their views on how GenAI adoption could enhance customer satisfaction and loyalty as a means to strengthen the banks position in an increasingly competitive and challenging market. Responses suggest that, although banks can significantly improve the customer experience by offering tailored products and personalised services, achieving this necessitates a careful balance between technological integration and RM intervention. This feedback is explored below, focusing on aspects of personalisation, digital enablement, and maintaining the human touch.

4.3.2.1 Personalisation

Participants acknowledged that banks could provide a heightened level of personalisation and tailored financial offerings to customers through leverage of predictive analytics and data-driven insights. Traditionally, RMs would need to sift through vast amounts of data and statements to understand their customers’ financial health. According to P8, Bank X has created enablement for RMs through implementation of data aggregation tools like Smart2, Bizflex, and Proact, to automate and aggregate manual processes. These tools gather data from different platforms, providing detailed insights that assist RMs in creating a more accurate view of each client's financial profile.

> *"You'd have to go into the customer bank statement, interrogate what transactions are going off his account … paint a picture of the client from there. Now, Smart2 obviously pulls all the data from every other system that relates to banking or leads to the clients and give you that data on the platter."* ***- P8***

This capability not only enhances RM's ability to offer personalised products but also fosters a sense of understanding and partnership with clients. As mentioned by P8, this data-oriented approach eliminates "blinker-driven" selling and allows for more nuanced discussions about applicable banking products and services.

Participants further believed that GenAI's ability to anticipate when clients might need loans or financing solutions will facilitate proactive communication with customers, creating a win-win situation. P9 suggested that foresight empowers clients to approach RMs with a comprehensive understanding of their portfolios, which streamlines discussions and enhances the overall experience.

> *"I don't want to be looking for ways to position everything to my client if he can get this data proactively through our systems and it keeps him keeps his mind at ease in knowing that the bank is there to support him. It just makes for easier portfolio growth for the future."* ***- P9***

P7 highlighted that RMs could benefit from real-time alerts and insights that reveal suitable lending options based on current customer dynamics. P8 further emphasised that early fraud detection could also significantly contribute to customer trust and loyalty, fostering a sense of being prioritised and supported.

> *"The proactive engagement, we are actually going to be detecting fraud and security issues before they happen. The customers would love this very much*

because we would be helping them to protect their accounts and this builds trust with the bank's ability to safeguard their assets." **- P8**

Overall feedback from participants suggest that enhanced personalisation and proactive engagement leads to a more satisfying and seamless banking experience for customers, which in turn encourages loyalty and long-term relationships. This view is echoed in the literature of Singh and Singh (2024), Dhake *et al*. (2024) and Sharma *et al*. (2023), who all highlight the potential for GenAI to provide personalised guidance to customers, with tailored recommendations and financial advice based on their individual situation and needs. This can help customers better understand their options and make informed decisions.

4.3.2.2 Digital enablement

Apart from participants believing that GenAI could positively influence customer experience through enhanced personalisation, they also felt that it had the added potential to digitally enable customers through its advanced features and cutting-edge technology. P2 spoke about advancements like chatbots and virtual assistants that could provide instant responses to customer queries.

> *"If there's improved accessibility, where GenAI can provide 24/7 customer services by either chatbots or virtual assistants, it makes it easier for customers to get help when they actually need it." **- P2***

According to P10, this responsiveness is crucial in providing an optimal service to customers, especially for SMEs where swift decisioning is imperative to their success. They may, otherwise, opt for immediate offers from competitor banks instead of waiting on slower responses from Bank X.

> *"We're finding in this market the customers want answers immediately and you understand where they're coming from. With the SMEs, I need to answer by 10:00am failing which they are going to take the deal with Bank Y." **- P10***

P11 highlighted opportunities for enhanced customer self-service capabilities, suggesting that use of data-driven insights and digital tools could enable customers to request limit increases beyond the system-generated amounts and without the need for RM intervention. Another example mentioned by P11 was merchant service cross selling opportunities. If a customer needed to order point-of-sale devices, GenAI could enable the online procurement, both streamlining the process, as well as presenting opportunities to cross sell to merchants without RM involvement.

> *"If a customer is opening up a new Fishaway, he's gonna come through to the bank … I need two point of sale devices. But if he has the ability to apply for it online, we can improve on the cross sell for merchants."* ***- P11***

The above feedback is aligned with findings of Sharma *et al*., (2023) who recognised the potential for OpenAI's ChatGPT to improve operational efficiency and enhance customer engagements through the capability for human-like conversations with chatbots. This is further grounded in the empirical research conducted by Devan *et al*. (2024), who also surfaced the revolutionary capabilities of AI-powered chatbots and virtual assistants to offer instant tailored customer solutions.

4.3.2.3 Maintaining the human touch

While participants recognised that GenAI enhances operational efficiency through automation and streamlining of processes, they believed, however, that some customers still appreciate and prefer a personalised and tailored service from their RM over the generic responses provided by AI. P11 and P12 both referred to AI generated automated responses creating perceptions of an impersonal experience and the likelihood of customer frustration should interactions appear as robotic rather than personalised.

> *"Human touch is completely taken away. I'm speaking to a robot the whole time. Where is my relationship manager? There must be a mix of integrating the human level and digitisation."* ***- P11***

> *"Because not all customers want a machine to talk to, they want a personalised offering. They want to be able to chat to you and for you to give advice, not just provide a response, you know, the personalised touch." -* ***P12***

P8 elaborated that customers are already being spammed by call centres and expecting them to respond to system generated messages could exacerbate the frustration.

> *"You don't want AI to become that impersonal … call centres are calling 24/7 and they get so sick of it that they probably will not respond to the AI prompt."* ***- P8***

Additional feedback was that different customer segments may react to AI differently. P11 noted that younger, tech-savvy clients may embrace AI-driven service, while older clients might prefer more human interaction. The consensus was that technology challenged customers would probably struggle if they encountered complicated processes that a machine could not address effectively, raising the risk of alienation. Creating a balance between automation and the human touch necessitates the adoption of a hybrid approach, where AI handles routine tasks and RMs focus on relationships and handling more complex customer needs. This means integrating AI into the workflow to improve and enhance, instead of replacing the human role. The hybrid approach will be discussed further under *Strategies for successful integration* in Theme 3.

Overall feedback from participants was that, while AI can enhance efficiency, it will not fully replace the human role. The human touch remains invaluable, especially in fostering loyalty and trust among clients. This is supported in the literature with Accenture (Abbott, 2024) predicting that the banking experience will become functionally correct but emotionally void due to the loss of human interaction. Domokos and Sajtos (2024) cautioned that banks will lose the competitive advantage to differentiate as personal touch with customers diminishes, with Colgate and Lang (2005) adding that loss of the human touch would lead to loss of trust.

4.3.3 Alignment to theoretical framework

This section of the findings provided essential insights regarding the impact of GenAI on RM roles, as well as the broader implications for customer experience in the banking sector. Responses suggested the potential for GenAI to transform the existing RM role, leading to improved efficiency and enhanced personalisation. Participants raised concerns regarding job security and resistance to adoption, indicating the need for the RM to be trained in both interpersonal skills and technical skills. There was caution though against over-reliance on technology at the expense of personal interactions, with respondents highlighting the importance of balancing automation with the human touch. The suggestion was for banks to be practical in their adoption approach, maintaining personalised service while equipping RMs with the tools and training to thrive in an evolving landscape. This will allow for enhanced service offerings to customers that builds on trust and loyalty. Although there are many opportunities for RM efficiency improvements, the literature is limited in its understanding of customer perceptions to GenAI adoption, particularly in terms of how they rate automated responses compared to RM human touch. This will be discussed further in Chapter 5.

UTAUT2 alignment

Responses indicate that the transformative role of RMs with adoption of GenAI is influenced by various UTAUT2 factors. Technology integration provides both opportunities and challenges which require intervention.

Performance Expectancy: Feedback suggests an expectation that GenAI will enhance RM performance by automating routine tasks, thereby allowing for a greater focus on personalised, strategic client interactions. This aligns with the constructs anticipated improvements in job performance through technology adoption. This construct is well supported by the findings of Zegullaj *et al*. (2023) who observed that the integration of GenAI in banking will be primarily fuelled by a focus on customer-centricity as the RM role evolves. Devan *et al*. (2024) also noted that GenAI's ability to process extensive customer data would allow RMs to deliver customised recommendations. Kayode (2024) and Hamzah *et al*. (2016) further indicated that AI-powered chatbots and virtual assistants could foresee customer needs and handle inquiries, thereby enabling RMs to engage in more personalised conversations with clients. This transformation in the RM role is believed to foster stronger customer relationships and boost banks' revenue growth.

Effort Expectancy: Responses suggest that RMs may be apprehensive regarding the effort required to adapt to GenAI tools, particularly due to concerns around job security and the skills needed. If GenAI adoption is perceived as overwhelming, it may impede acceptance. Oracle (2021) support this construct where they also raised concerns about job security and resistance to change, underlining the necessity for change management for RMs. The literature advocates that banks should take a practical approach by equipping RMs with the right support for effective adoption of GenAI tools.

Facilitating conditions: Feedback suggests that some RMs may potentially resist adoption of GenAI due to their perceived lack of technology knowledge and skill. This suggests a need for AI competency training to equip RMs with essential skills needed for their role transformation. This feedback aligns with the observations of Accenture (2024), who posited that the banking sector must embrace new skills, strategies, and mindsets across all organisational levels to remain relevant in an increasingly digitally transforming landscape. Participants further emphasised the need to maintain a human touch, which reflects the complexities of service delivery in an increasingly digital landscape.

Social Influence: The varied responses towards GenAI adoption highlight a social dynamic among RMs - while some would be enthusiastic, others could fear job loss. This necessitates the need for effective change management strategies to foster a supportive environment for integration.

4.4 Theme 3: Opportunities and challenges of integrating GenAI

Theme 3 of this study sought to assess the opportunities and challenges of integrating GenAI into relationship management in bank lending. The following categories were identified: Integration opportunities, Integration challenges, and Strategies for successful integration.

4.4.1 Opportunities

The research findings from participant interviews indicate that GenAI has transformative potential in bank lending relationship management for improved efficiencies, personalised service, reduced costs and risk and fraud management.

4.4.1.1 Improved efficiencies

Responses indicate that a key driver is the potential for improved efficiency as a result of GenAI's ability to automate routine administrative tasks. Participants believe that through automation of manual credit application processes, RMs time would be freed to focus on more complex and personalised aspects of client interactions. P1 mentioned that this would not only speed up processes but also allow for more effective client engagement.

> *"For me a key driver would be efficiency and time saving. Less room for error, things will be done a lot quicker and it will be easier. It will actually enable us to spend more time with our client."* ***- P1***

P7 agreed, adding that the effort it takes to put together a personalised agenda for client engagement sessions is time-consuming and exacerbated further when RMs have multiple clients in a day.

> *"Build me a little pack that I could then present to the client, very personalised. You know that amount of research you've got to put in to do that ahead of a client meeting is immense. It is very difficult to manage two to three clients a day and have that level of detail for each client."* ***- P7***

P11 noted GenAI's potential for faster and more informed decision-making through its ability to quickly analyse data and provide actionable insights. This would serve to reduce the time taken to process and approve loans, resulting in improved customer service.

> *"Allows me to make a more quicker and informed decision for our clients. I think our response to the to the clients would be a lot quicker."* ***- P11***

Respondents further believed that automation could present the added benefit of reducing human error. This, in turn, would improve the overall quality and accuracy of the information shared with clients.

The feedback aligns with the findings of Krijger(2023), who recognised opportunities for automation, resulting in streamlined operations, improved decision making and time savings. Domokos and Sajtos (2024) also recognised the transformative potential of GenAI to significantly enhance customer experience and drive revenue growth for banks to remain competitive in the digitally evolving consumer market.

4.4.1.2 Personalisation

Participants mentioned GenAI's ability to analyse vast amounts of data as an enabler for more personalised recommendations to customers. P7 believed that identification of customised offerings, that could have otherwise been missed, would improve engagement and enhance customer satisfaction and loyalty in a very competitive market.

> *"Banking is difficult as it is right now. We need to look after the clients we have. We need to grow our market share. We need to know our clients intimately with their unique needs and provide that personalised offering."* ***- P7***

P9 added that GenAI could potentially open up new markets and product offerings through leverage of automation. The example given was automation to streamline the loan documentation processes, thus allowing the bank to enter previously inaccessible or under-served markets and ultimately increase revenue.

> *"AI will also be able to open new markets that we might actually not have been able to penetrate."* ***- P9***

Participant views is supported in the literature with Singh and Singh (2024) recognising the potential for data-driven insights to offer tailored advice to lending customers based on their specific financial needs. This would ultimately aid in better understanding options to make more informed decisions. The findings of Bhatore *et al*. (2020) also suggested that data-driven insights would assist in removing bias and subjectivity from the decision-making process.

4.4.1.3 Cost reduction

Additional feedback highlighted that the efficiencies brought about through automation could lead to considerable cost reductions in operations, customer service and compliance. P7 substantiated how this could lead to reduced service costs, resulting in lower fees for customers. Tasks that previously required considerable manual resource management time could now be accomplished at a fraction of the cost through automation. P2 added that this could result in operational cost savings over time, especially in areas like loan origination and document processing.

> *"Cost reduction is a big one because over time the automation and efficiency improvements provided by the GenAI can lead to significant cost reductions in your operations, your customer service and compliance spaces." - **P2***

The case studies of HSBC (White, 2021) and DBS Bank (2023), referenced in the literature aligns with this thinking. Both banks implemented AI solutions to automated routine transactions which also served to reduce costs and overall enhance the customer experience. McKinsey (2021) and Accenture (Abbott, 2024) further highlighted that banks leveraging AI in lending operations would reduce costs and increase revenue.

4.4.1.4 Risk and fraud management

Another area of opportunity mentioned was risk assessment and fraud prevention. Feedback from P2 indicated that GenAI could potentially improve risk assessment through data-driven insights. The respondent suggested that adoption could improve credit scoring models through the integration of traditional and non-traditional data sources, thus improving the accuracy of credit evaluations and reducing defaults.

> *"We use AI in the modelling of credit risk and operational risk by generating predictive insights, which is helping the bank to make better informed decisions to minimise the risk." **- P2***

P3 further mentioned that GenAI could be valuable in fraud detection due to its ability to recognise patterns and irregularities in transaction data, thus helping to identify and mitigate fraud.

> *"We can also use it in risk assessment and fraud detection. By analysing vast amounts of data, identify patterns and anomalies which can be an indication of fraudulent activities." **- P3***

The above findings are supported in the empirical research of Sharma *et al*. (2023) who demonstrated how AI models can effectively reduce risks in credit assessments and loan authorisations. Bhatore *et al*., (2020) alluded to the potential for fraud detection and mitigation through effective data-driven insights, which further support the interview findings.

4.4.2 Challenges

While AI offers multiple opportunities ranging from increased efficiency to improved customer satisfaction, it also introduces challenges related to data quality and bias, loss of human touch and job displacement.

4.4.2.1 Data quality and bias

Participants responded that the effectiveness of GenAI in bank lending hinges significantly on the quality of the data used. Accurate and robust data, including images and videos. is mandatory for optimum results across all platforms, Poor data ultimately means poor results. P3 likened this to the "garbage in, garbage out" principle, suggesting that AI lacks the human-like understanding to correct user errors in input, resulting in erroneous outputs. This could lead to customer frustrations and reputational damage for the bank.

> *"It's also important to point out that the quality and reliability is based off the information that is actually being consumed by the AI. So, if the information is garbage, it will be garbage in, garbage out." **- P3***

Another concern raised was the potential for 'hallucination' or false information, which often depends on how questions are posed to the system.," P1 referred to this as prompt engineering, asserting that poor prompting, i.e., asking vague or ambiguous questions, would return incorrect results. The respondent indicated that this could be exacerbated by AI models being trained on inaccurate data, and that successful GenAI implementation requires high-quality, well-integrated data. It is essential to address this issue, as poor outputs would result in unfavourable customer experiences.

> *“This whole issue of prompt engineering and how do you restrict what data is being used and how the questions are being asked in such a way that you reduce hallucination, or false information out.” **- P1***

An added concern is the introduced bias into the system. Many AI models, particularly those developed in Western contexts, may exhibit biases leading to unfair treatment of various population groups. This concern was echoed across several participants, particularly in credit scoring, where the potential for perpetuating existing biases would be heightened if AI systems are not properly trained and monitored. P6 cautioned against the risk of reputational damage associated with mismanaged AI applications if customers perceive bias in the decision-making processes.

> *“Until we deal with the bias and the hallucinations from an AI perspective, we need to be very careful in the way that we introduce AI to our customers.” **- P6***

P6 substantiated by cited the example of a company that faced backlash for racially biased loan approvals.

> *“There was a company in the US that took Amazon Bedrock and implemented it within the organisation and the model started giving loans to certain people and were rejecting certain people based on skin colour.” **- P6***

P5 highlighting another key challenge faced by organisations, including Bank X, which is the general lack of understanding on how to effectively incorporate large amounts of data into GenAI models. This is due to the technology being fairly new in banking and lacking maturity.

> *“One of the key drawbacks …is processing large amounts of data. So yes, GenAI is taking the world by storm, but at this point in time, I think it's so new that we haven't quite figured out how to take large amounts of data and embed it within a GenAI model.” - **P6***

The feedback provided is in alignment with the findings of Oracle (2021) where GenAI’s potential to inherit and amplify existing biases was surfaced. This was further supported by Domokos and Sajtos (2024), who voiced that due to the tool learning from historical data, existing biases would be exacerbated and carried forward, resulting in compromised decision-making. Matsie (2023) also cited an instance of discriminatory loan application rejections within a specific demographic group, echoing P6's example of Amazon Bedrock. The feedback was that effective governance frameworks is critical for managing how AI is utilised, especially concerning compliance and regulatory reporting. This will be discussed further under *Strategies for successful integration* in Theme 3.

4.4.2.2 Loss of human touch

A common sentiment across respondents was the concern of loss of human touch in banking with the increased use of AI. Participants feared customers may feel alienated if they perceived communications as being automated rather than coming from an RM.

> *“They would definitely be frustrated and it would eliminate that personal touch. Some clients really, really enjoy personal touch.”* ***- P10***

P11 responded that clients could become frustrated if they felt that they were interacting with machines instead of real bankers, emphasising that many customers prefer personalised, human interaction, especially for sensitive financial matters. This could thus lead to the risk of an impersonal and negative customer experience.

> *“Banking is very sensitive … close to the customer's heart. So, your finances is a very sensitive topic and maybe you do want to speak to somebody and not speak to a robot.”* ***- P11***

P11 further highlighted the importance of adapting to diverse customer preferences - some may be more tech-savvy, while others require more direct assistance. All would at some point require the personalised human touch.

> *"We've got tech savvy clients, we've got non tech savvy clients, so it's a mix. Some will love it. Some will hate it. I think at the end of the day even if they can do it, I think sometimes they still want that human element."* ***- P11***

Feedback from participants is supported in the literature with Accenture (Abbott, 2024) noting that although GenAI adoption will cause the overall bank experience to be functionally correct, it will become emotionally void with the loss of the human role. Colgate and Lang (2005) professed that this would ultimately lead to loss of trust in banks' ability to provide an optimal client experience. The research has observed that existing literature has a single-dimension view of technology replacing human roles and is limited in its understanding of how this adoption actually impacts the RM role. P6 suggested a *recommendary* approach where AI would recommend a decision and swivel chair, with handoff to an RM, who would then review the recommended decision and adjust any biases before granting final approval. This approach will be discussed in Chapter 5's *Recommendations*. Overall feedback was that a balance must be struck between automation and personal service to maintain trust and loyalty. This will be discussed further under *Strategies for successful integration* in Theme 3.

4.4.2.3 Job loss

There was concern raised regarding the potential impact of AI on job displacement. According to P3, manual administrative tasks could be taken over by automation, leading to jobs becoming redundant and RMs losing their jobs.

> *"AI can also lead to job displacement. The mundane tasks were actually being done by individuals. So, what we might see in time, is certain jobs being taken over by AI and those jobs become redundant and those people ending up out of a job."* ***- P3***

Another interesting comment raised by P3 was that the threat of job loss could result in an added challenge - reluctance to adopt digital technology.

> *"People sometimes when it comes to these technologies, say ah no, is it replacing my job, and then they are not really supportive." -* ***P3***

Ooi *et al*. (2023), supported this, stating that RMs in particular, would be resistant to adoption due to the fear of losing their jobs to automation. Existing literature, however, lacks in-depth knowledge of why RMs actually resist technology adoption. RMs interviewed clarified this, stating that while some believed GenAI would take away their jobs, others are actually resistant due to them not having the necessary skills to use the technology effectively. This gap in literature is addressed in Chapter 5.

4.4.2.4 Data privacy

The use of AI raises significant concerns about the privacy and security of sensitive customer data. A major challenge is gaining authorised access to customer information due to POPIA regulations. Participants raised the risk that data leaks or misuse could lead to severe consequences for both the bank and the customer.

> *"There are also issues around security and privacy. AI can pose security and privacy risks if particularly sensitive data is involved."* ***- P4***

P2 emphasised the need for stringent data security measures owing to the large amount of data that passes through the banking system. This raises the risk of potential data breach.

> *"Obviously there's a high focus on that in our banks because you are reliant on large amounts of data and there could be concerns about the data privacy and security."* ***- P2***

The findings of Singh (2024) align with this view, noting that GenAI can also present its fair share of challenges regarding concerns over data privacy. Interestingly, Krijger (2023) elaborated that data protection regulations requiring POPIA consent from customers for access, is sometimes a blocker to optimum usage of the data. Accenture (2017) shared the same view, claiming that this is the reason why only 5% of banks worldwide have adopted AI successfully into their functions, with the rest citing data privacy and other integration challenges as being inhibitors.

4.4.3 Strategies for successful integration

Feedback from participants revealed several viable approaches that banks could adopt to navigate the challenges raised in the previous section. These include a robust data strategy, strong governance and regulatory frameworks, a hybrid model approach and, continuous training and change management.

4.4.3.1 Robust data strategy

Participants responded that the effectiveness of GenAI in bank lending hinges significantly on data, but more specifically, the quality of the data used.

> *“Generative AI without data is nothing. So, it's the data integration and the data quality and validation.”* ***- P1***

P1 added that ambiguity needed to be eliminated in training data to enhance its quality. This requires careful curation and a structured approach to data governance and training.

> *“If we can get to that point where we start removing ambiguity, we improve the quality of what we're training on and we improve the context sensitivity. So, curation of data into the training model and an entire discipline of governance and training and enhancement.”* ***- P1***

P6 proposed that adopting an AI recommendation strategy, rather than fully automating the process, could help enhance the data quality until it reached a suitable level of maturity for full automation. This approach would involve handoffs where the tool would recommend a decision and then swivel chair to an RM for review. The RM would validate the recommendation and eliminate any biases before approving the final decision. This process ensures that the data is accurate and leads to informed decision-making for customers.

> *"We don't have to take AI and integrate it into our system to a point where it's updating our data. We can go the recommendation route, where we still have our users analysing what AI has brought out and validate and update manually.*"
> **- P6**

Accurate and robust data is mandatory for optimum results across all platforms, including images and videos. Feedback is that challenges of access and training of data can be addressed through the adoption of robust data strategies by the bank, which should include a data governance framework and data training controls amongst others.

Data Governance Framework

Participants proposed the establishment of clear governance frameworks which would include setting of standards for data accuracy and security. P1 recommended the implementation of processes for continuous data validation and cleaning of the data. This would ensure that the data used in GenAI models is accurate and reliable. Proper curation of data is mandatory for AI's contextual understanding and its ability to reduce hallucination.

> *"So, if we can get to that point where we start removing ambiguity, we improve the quality of what we're training on and the context sensitivity. So, curation of data into the training model and an entire discipline of governance and training and enhancement." **- P1***

P2 added the need for effective data protection measures involving human oversight and regular audits.

> *"We require governance and oversight to control those AI initiatives … make sure that we've got robust data protection measures in place."* ***- P2***

Data training controls

Respondents suggested the need for diverse training datasets that reflect various customer profiles and lending scenarios. P1 highlighted the importance of refining training data to minimise ambiguity. This would help ensure that training models are robust and can generalise effectively. P1 further proposed the adoption of small language models over large language models to solve for the issue of ambiguity in the training. Small language models are deemed to be more purpose built to learn and train on smaller, specific data sets in a focused way.

> *"The big trend I would see is ultimately, smaller language models, not necessarily the large language models. A smaller model that's much more purpose built, much more focused and trained on relevant information and removing ambiguity from your training."* ***- P1***

P6 suggested that, during this establishment phase, it would be more prudent for the bank to utilise GenAI as a recommendatory tool rather than full automation adoption. This would allow for the tool to be trained and corrected, with RM oversight, and without reputational damage, until the system matures and demonstrates reliability.

> *"Rather do AI recommendations at this point … we still keep our human element where we can look at and adjust the biases accordingly. And until we get to a point where we've taught AI enough, where we've run our data through the models enough, where those hallucinations and bias start reducing, we then will be able to take AI and implement it in our systems, but until then, I think recommendation might be the better way until we get to a point where we are more mature."* ***- P6***

Overall feedback was that adoption of a robust data strategy, centred on quality, accessibility and data training controls, could more effectively help banks leverage GenAI in their lending divisions. This strategy would, not only address the challenges of data management, but also pave the way for enhanced decision-making and improved customer experiences. Literature reviewed in this study aligns with participant findings. Oracle (2021) and Domokos and Sajtos (2024), recognised that AI algorithms can introduce ethical challenges of inheriting and amplifying existing biases which could result in unfair decision-making in bank lending. The study showed that the concerns about ethics and privacy emphasised the need for purpose driven data strategies addressing issues of data credibility and data protection.

4.4.3.2 Governance and regulatory framework

Participants believed that the risks to data privacy and security raised in the previous section could be addressed through strong and robust governance and regulatory frameworks. This would include risk and compliance awareness controls and data security protocol.

Risk and compliance awareness

P1 advised that banks need to be cautious in exposing GenAI solutions and must ensure that AI derived decisions can be substantiated. He cautioned against uncontrolled use of the technology, indicating the need for strong governance mechanisms to oversee the risks involved in its adoption.

> *"It's that power without control thing is a little bit of a concern…how it will be adopted, I think there's going to be a lot of experimentation and then a lot of work on the governance and control side of how it gets applied."* ***- P1***

P2 concurred, stating that the banking sector is a heavily regulated industry and that banks needed to comply with the structured guidelines set out by the Non-Financial Risk (NFR) teams to ensure responsible use of the technology.

"NFR teams that provides guidelines for using GenAI. All these risks are captured into the guidelines to make people aware of how to use AI in a responsible way ... regulatory compliance and risk assessment as banking is a highly regulated industry." ***- P2***

Interestingly, though, P9 believed that banking is overly regulated and being inflexible actually hinders optimal delivery to clients on time.

"Sometimes our processes prohibit us from really delivering to a client or we've got so much red tape that you have to jump through hoops to actually just get something done…we've got a rule book and the rule book is not flexible." ***- P9***

Data security protocol

Feedback indicated that strong focus on data security and compliance with POPIA regulations is crucial for successful integration of AI. P5 indicated that Bank X had existing governance in place which would now need to include data security controls for the responsible and ethical use of AI, ensuring protection of customer data.

"The use of customer data for training AI models can raise ethical and regulatory issues. We have governance and oversight to control those, make sure that we've got robust data protection measures in place." - ***P5***

P9 added that ethical considerations must be integrated into the design and adoption to ensure fairness, transparency, and accountability. Addressing the complexities of different stakeholders is essential for building trust and ensuring ethical use of the technology in banking.

"How it's designed … and all the risk factors that have to be considered and all sort of requirements with POPIA … how to interact with different product houses or stakeholders." ***- P9***

Overall feedback is that the successful integration of GenAI into bank lending will hinge on a well-defined strategy encompassing solid governance and compliance, with commitment to protecting customer data. The feedback aligns with the findings of Accenture (Abbott, 2024) who recognised that banks need to maintain clear accountability for AI-driven decisions that will impact customer experience. P2's observations that banking is a highly regulated environment, is supported by the findings of Kaushal (2024), who also recognised the need to comply with data protection and governance regulations to protect customer data. Krijger (2023) concurred, adding that the large amount of customer sensitive data required to effectively train models often proves challenging to access securely, and therefore requires robust data security governance measures.

While existing literature recognises the importance of AI and data governance frameworks, there is a lack of comprehensive, industry-wide frameworks that specifically address ethical AI reporting practices in the bank lending, given the complex credit decisioning processes. This research addresses the gap in Chapter 5 *Recommendations* by prescribing guidelines on data privacy, algorithm auditing, and promoting transparency in AI-based decision-making processes.

4.4.3.3 Hybrid model

Participants believed that the challenge of loss of human touch, due to GenAI integration, could be overcome by adopting a hybrid model approach. According to P2, this is where GenAI would serve as a support tool that aids RMs in providing more personalised service, rather than taking over their roles entirely.

> *"I think hybrid models combining AI with human oversight, a guideline that says you cannot use AI in any situation where they have to take a decision on a customer. The responsibility still lies with the RM, and the RM can use GenAI as an assistant."* ***- P2***

> *"I don't think in business banking you can ever replace RMs, so AI will only be a support that would actually enhance their job."* ***- P3***

P11 responded that customers prefer personal interactions with their bankers over automated communications, re-iterating that maintaining a human touch is essential for building trust and loyalty. Customers may feel alienated if they perceive their interactions as entirely computer-generated.

> *"So, in terms of trust and loyalty, we can't have a situation where the human touch is completely taken away, because then the client is going to feel OK, so I'm speaking to a robot the whole time. Where is my relationship manager? So, there must be a mix of integrating these two, which is the human level and then the digitisation."* ***- P11***

A successful hybrid model would require defining which tasks would be automated and where human involvement would be necessary. Participants also stressed the need for RMs to validate AI-generated information, ensuring accuracy and responsiveness to customer needs. P3 recommended training for RMs on how to use AI tools, and a clear framework outlining the roles of both AI and RMs, as being vital to the success of the hybrid model.

> *"Training is important, but at the same time you need to have a clear engagement model between what interactions the RM will do and what the AI will do,"* ***- P3***

There was consensus across all participants that while AI could enhance banking experiences by automating and streamlining tasks, it should ultimately support and empower RMs, rather than replace them. Maintaining this balance is essential to continually serve clients effectively and meet their diverse needs.

Overall, the findings suggest that the hybrid model approach of blending AI efficiency with human oversight could solve for the challenge of loss of human touch, thereby providing an optimal customer experience in bank lending. This is supported in the literature, with McKinsey (2023) and Deloitte (2024) both suggesting that the technology could potentially augment the RM role rather than replace it. McKinsey (2023) further suggested that banks could use MS Copilot to assist RMs in providing better customer service. Copilot's ability to analyse customer data quickly and efficiently, and recommend solutions timeously, will allow for RMs to have quicker and more personalised customer interactions. Bankwell Bank's example of adopting Cascading AI's software, Casca, to act as a virtual assistant to RMs, is another example supporting the findings (Crosman, 2024). The literature of Mossavar-Rahmani and Zohuri (2023) further aligns with participant feedback, suggesting that the role of the RM could be transformed to that of a trusted advisor who will leverage AI to provide a better customer experience. The literature, however, is limited in findings of how customers themselves perceive GenAI adoption by the financial institutes that service their banking needs, specifically in terms of fully automated services over RM intervention. This gap will be addressed in Chapter 5.

4.4.3.4 Training and change management

Participants believed that the fear of job loss and resistance to change could be remediated with proper training and change management. Training would entail both soft skills for adaption to the technology, and then more focused training on how to use the tool effectively.

Soft skills

P4 believed that RMs may initially feel threatened by the technology and asked for clear establishment of engagement models between RMs and GenAI systems, along with effective communication about the technology's role. This soft skill training could help reduce resistance and foster adoption of GenAI.

> *"We need to have a clear engagement model … between what I do and what the AI will do. Not that it should replace my job."* ***- P4***

P3 supported this view stating that the training required should focus on how to utilise AI to enable their roles, adding that the human touch was essential for successful integration.

> *"The kind of training they might need is how to best leverage AI to best support them in their job, to actually be able to augment them, because that human interaction is still necessary in our space."* ***- P3***

P2 suggested that, as GenAI takes over routine tasks, RMs should focus on enhancing soft skills like empathy, communication, and relationship-building to navigate complex customer interactions effectively. P6 rolled this up to an organisation view, stating that it is important that the bank as a whole is taken along on the AI journey. This suggested that the collective effort would strengthen the overall ability of the bank to adapt to AI technologies.

> *"It's a focus area that I feel we need to look at … it's important to not only do the POCs but take the rest of the organisation along with us ... how do we as a bank take everybody that works within the organisation to a point where we are moving together and assisting the organisation."* ***- P6***

AI technology

Apart from soft skills for acceptance of the technology, participants also alluded to additional training that may be required to teach RMs how to use AI tools effectively. Previous feedback suggested that not all RMs are tech savvy and this could be a contributor to change resistance. P4 suggested that this approach to training, where AI literacy is taught to non-tech savvy users, could alleviate frustrations and foster change acceptance.

> *"It also requires that we change the way we manage employees to ensure that they are adequately trained and can adapt to the new technologies and workflow. Sometimes technology frustrates."* ***- P4***

Additional feedback across participants was that RMs will also need to learn how to effectively collaborate with AI systems. This would include an understanding of how to integrate AI suggestions with their own insights and how to manage the ethical considerations to avoid biases in automated decision-making. P6 emphasised the importance of providing RMs with proper training in prompt engineering to reduce false output and hallucination. He illustrated this point by sharing his own experience, which he credited to enabling him to effectively adopt and utilise GenAI in his role. The rationale behind this suggestion is that mastering the skill of formulating effective prompts with high-quality input directly impacts the usefulness of AI output, ultimately mitigating hallucination.

> *"One of the biggest things that I did that I think enhanced the way I looked at AI was taking a course on prompt engineering. And I felt like doing that allowed me to utilise AI to a better potential in the sense that's very similar to you know this phrase, garbage in garbage out … if you don't prompt AI correctly, the output that you get from AI is not always beneficial and it also may hallucinate from that." -* ***P6***

P1 had almost identical feedback, advocating for prompt engineering training for RMs, although not having personally undergone any such training.

> *"There's a sort of language and prompting dimension that they're going to have to teach people to how to use it productively and effectively."* ***- P1***

P2 added that the integration of GenAI would require continuous experimentation and adaptation. Training should foster an environment where employees can learn from experiments, including mistakes, and iteratively refine their use of the tool. This would lead to enhanced adoption and collaboration.

Change management

Participants spoke about the need for effective change management strategies to ease the transition to data-driven decision-making, promoting a culture that embraces innovation and adoption. Included in this would be transparency in communication, formalised structures and supportive processes for experimentation and learning.

P2 spoke about the necessity for banks to provide clarity to employees regarding AI adoption strategies. This could assist in alleviating change resistance resulting from fear of the unknown.

> "*Transparency and education is what needs to be driven in the bank. We all need to know what the strategy is in how we will use it, what are those*

processes and what we will use to govern these things. Not understanding how AI works exacerbates fears and all trust issues.” - ***P2***

P6 indicated that GenAI integration would only be as effective as the value it added to the person using the technology. The ease of use and integration is paramount to successful adoption. This again hinges on AI literacy education for the workforce as part of an effective change management strategy.

“But the greatest learnings I had … no matter how much automation you have, if the next person cannot use what you built, then it’s useless. It needs to be so integrated that it becomes easy for the users to be able to pick it up and use it. And that is what makes successful integration technology into AI.” ***- P6***

A further perspective from P1 was that change management should include education and awareness about the potential risks, limitations, and governance issues associated with the tool. This includes recognising that GenAI is not a catch-all solution and requires deliberate thought and consideration in its adoption.

"One of the major disadvantages of GenAI is a general misunderstanding that it is a silver bullet to any problem that we get, it can solve anything. It is getting an enormous amount of attention and people are trying to apply it sometimes in places where it doesn't fit. And so, I think there's a bit of an opportunity cost there that the bank is missing.” ***- P1***

P2 emphasised that creating a dedicated division for GenAI within the bank would help manage risk and set expectations for the use of the technology. At present, Bank X's GenAI initiatives are often viewed as secondary or passion projects, potentially hindering progress, compared to competitors who are more heavily vested in AI adoption. This implies that strategic focus on adoption should be established from the top down as part of the change management process.

“We don't have a formal structure for AI. Everybody that is involved in AI currently has to contribute in their own spare time, so it's a passion work.

I think the risk is other banks will precede us because we not giving dedicated resources to AI. We should have a whole division dedicated to AI.” - ***P2***

Overall feedback suggested that the successful integration of GenAI into bank lending is dependent on soft skills and AI technology training for RMs, supported by effective change management processes. This feedback aligns with the literature of Miah (2024) who recognised that RMs would require upskilling in communication and interpersonal skills, as well as data analysis and interpretation, to adapt to their transforming roles. Accenture (2024) corroborated, suggesting that new skills, approaches and mindsets will be needed, in every function and level of the bank.

4.4.4 Alignment to theoretical framework

The feedback from participants in Theme 3 revealed that GenAI has the transformative potential to improve efficiencies, enhance customer experiences, and provide more personalised services. Participants further acknowledged that, whilst GenAI offers these opportunities, it faces challenges of data ambiguity and bias, loss of personal touch to customers and RM resistance to adoption. Participants suggested that banks could overcome these challenges through the adoption of robust data strategies, governance and regulatory frameworks, a hybrid model approach and, effective training and change management. These findings are supported and can be validated in the literature reviewed as part of this study. Whilst the existing literature primarily focused on theoretical frameworks and potential advantages, there is insufficient insights to address the practical challenges that impede implementation, such as RMs resistance to adoption due to lack of GenAI skills. The gaps and interventions will be discussed further in Chapter 5 *Recommendations*.

UTAUT2 alignment

Theme 3 feedback aligns with the constructs of UTAUT2, focusing on several key areas. It surfaces *performance expectancy* by showcasing how GenAI can enhance efficiencies, offer personalisation, and reduce costs in banking. Additionally, it addresses challenges related to *social influence* and *facilitating conditions*, particularly concerning training and data governance. There was a strong emphasis on balancing AI with human touch, to mitigate fear of job loss and resistance to change.

Performance Expectancy: Participants indicated that GenAI could automate routine tasks, leading to quicker processes and more effective client engagement, thus improving efficiency in relationship management. They further recognised the tool's ability to analyse large amounts of data for tailored recommendations, which enhances customer satisfaction and loyalty. This reflected a belief that the technology would improve performance in customer service delivery. Participants also highlighted potential cost savings resulting from increased automation, which translated to better financial performance for the bank. The works of Kayode (2024), Mossavar-Rahmani and Zohuri (2023), and Sharma *et al*. (2023) support the construct by highlighting the potential advantages of GenAI adoption in banking, particularly in lending. These benefits include enhanced operational efficiency, product personalisation, cost savings, and improved risk and fraud management. This is backed by the empirical research of Devan *et al*. (2024), who identified prospective advantages of predictive analytics in areas such as customer service, tailored banking, credit assessments, and operational efficiency. The research of Bhatore *et al*. (2020) suggests that AI-driven chatbots and virtual assistants could significantly enhance customer experiences through personalisation and customised lending solutions.

Effort Expectancy: Feedback indicated that effective training on both soft skills and using AI technology was essential. This suggested that while participants saw value in GenAI, they also recognised that successful integration required mitigation of steep learning curves. This construct is further supported by the findings of Miah (2024) who noted the upskilling that RMs would require to adapt to their evolving roles. This would include soft skills like communication and interpersonal skills, as well as technical skills like data analysis and interpretation.

Facilitating Conditions: Feedback emphasised the importance of robust data strategies and governance frameworks. This aligns with the construct, as organisations would need to implement structures that ensure the availability of high-quality data for GenAI systems. The feedback is supported in the literature by Domokos and Sajtos (2024), who proclaimed the importance of rigorous data protection and governance measures, arguing that the responsible application of AI in banking is vital to mitigating risks and biases in results. Furthermore, the suggestion for dedicated departments within the bank recognised the need for appropriate resources and infrastructure to support successful integration.

Social Influence: Concerns regarding job loss was prevalent across participant feedback. This indicated that social influences, such as peer concerns about job security and organisational culture, play a significant role in the perceived acceptance of GenAI. The findings of Ooi *et al*. (2023), support this construct, with the authors highlighting that RMs who feared losing their jobs would potentially resist adoption. Addressing these issues through effective communication and training could increase acceptance.

Overall, the integration of GenAI into bank lending could positively impact acceptance and use of the technology, if executed carefully with focus on training, governance, and performance management.

4.5 Conclusion of findings

This chapter aimed to present and discuss the interview findings as was applicable to the research objectives identified. It commenced with an overview of the participants involved in the research, then addressing the current challenges that RMs experience with inefficient manual processes and poor data utilisation in bank credit lending. The discussion went on to detail the opportunities for automation and innovation, focusing on the transforming RM role with the adoption of GenAI. The challenges of integrating the technology into bank lending were then presented and discussed, including issues such as data quality and bias, loss of human touch, and job displacement. The chapter concluded by proposing strategies for the successful integration of GenAI into relationship management practices, drawing on relevant literature to support the findings presented and discussed.

CHAPTER 5. CONCLUSION AND RECOMMENDATION

This chapter synthesises the research findings applicable to each of the three propositions outlined in the study, evaluating whether the objectives for each were successfully achieved. The analysis compares the literature findings with the insights gained from interviews, providing clarity to validate or refute the study's outcomes. Gaps in the literature are then surfaced together with the research contributions to address the short fallings. Focus then moves to the study's contribution to the theoretical framework as well as new insights gained. The chapter ends with recommendations for stakeholders and cases for future research.

5.1 Introduction

The purpose of this study is the understand the impact of GenAI on bank RM roles and customer lending experiences. Literature reviewed in chapter 2 suggest that GenAI adoption in the financial industry has surged in recent years due to opportunities for streamlined operations, improved decision-making, reduced cost and enhanced client experiences. (Krijger, 2023). The study extends the above findings at product level to determine whether GenAI adoption additionally influences customer experience provided by RMs in bank lending.

Literature findings recognise that GenAI is a fairly new concept pioneering in the banking space, with limited research on its impact on RM roles and lending customer experience. The below gaps were identified:

- limited empirical evidence on the integration of GenAI into relationship management roles
- limited understanding of the evolving role of RMs in the AI era
- scarcity of research on the practical challenges and opportunities of implementing AI technologies in bank lending.

The purpose of this research is to bridge the gaps identified in the literature through interview findings and recommendations, thereby enhancing existing academic knowledge and advancing understanding of GenAI adoption in bank relationship management.

The conclusion of the findings as they relate to each of the objectives below, will be discussed.

Objective 1: To analyse the impact of GenAI on the credit lending process and product personalisation in bank lending

Objective 2: To explore how the role of RMs evolves with the adoption of GenAI and its effects on customer experience

Objective 3: To identify the opportunities and challenges of integrating GenAI into relationship management within the banking sector.

5.2 Research objective 1 conclusions

Research objective 1 sought to analyse the impact of GenAI on the credit lending process and product personalisation in bank lending. Proposition 1 suggested that, through automation and innovative adoption of GenAI technologies, banks could revolutionise their credit lending processes and product personalisation offerings to improve customer satisfaction and drive economic growth.

5.2.1 Literature findings

Existing literature recognised the challenges experienced by RMs in the current credit lending cycle to include time-consuming, manual and inefficient credit processes (Palaparthy & Pillalamarri, 2015). Mehdiabadi *et al*. (2020) also noted lengthy processing times and high rejection rates with current loan application processes, while Sadok *et al*. (2021) mentioned biased decision-making.

Sharma *et al*. (2023) suggested that GenAI adoption could streamline credit lending and reduce processing times through automation of manual document gathering, verification, and underwriting. Tad *et al*. (2023) proposed that automation through AI and ML technologies could solve for manual and lengthy processes, while Kayode (2024) and Kalia (2023) suggested that big data and predictive analytics could be used to determine creditworthiness, generate more accurate credit risk profiles and optimise the loan approval process. Singh and Singh (2024) added the ability for personalisation and tailored recommendations to customers through predicative analytics while Bhatore *et al*. (2020) proposed data-driven insights to remove bias and subjectivity from decision-making.

The literature highlighted many opportunities for GenAI adoption, suggesting that banks leveraging transformative technology would overall improve the credit lending experience for both RMs and customers alike.

5.2.2 Interview findings

The interview feedback pertaining to Objective 1 had interesting insights regarding the integration of GenAI into bank credit lending processes with participants recognising the critical challenges faced by RMs i.e., manual processes, data access and retrieval and credit scoring inefficiencies.

Challenges

Manual processes: Document preparation by RMs for loan applications and credit approvals was noted as being manual, time-consuming and prone to error. Most respondents expressed that automation could significantly reduce the administrative burden, thus increasing productivity and client engagement.

Data access and retrieval: Accessing and utilising existing data emerged as a challenge due to the complexity and inefficiency of current credit processing systems. Several participants indicated that inefficient processes hinder decision-making, highlighting the need for more streamlined information retrieval.

Credit scoring: Participants pointed out challenges related to credit scoring, particularly the subjectivity and inefficiencies resulting from traditional risk management approaches. Instances of fraudulent documents presented by clients further complicate accurate assessments.

Feedback from participants suggested that GenAI adoption could potentially transform these challenges into the opportunities listed below.

Opportunities

Enhancing operational efficiency: Automation of routine, low-value tasks could free up RMs to redirect their efforts toward more strategic responsibilities, thereby increasing overall efficiency.

Improving credit scoring and risk management: Advanced data analytics could refine credit assessment processes, mitigate biases, and enhance the decision-making quality through real-time data evaluations.

Product personalisation: Customised lending solutions developed through data-driven insights obtained from customer data could significantly improve client satisfaction and promote long-term loyalty.

5.2.3 Gaps identified in the literature

While the depth of insights provided in the literature holds true for Objective 1 and supports the potential for GenAI to automate credit processes and enhance product personalisation, there is limited knowledge in the literature that addresses algorithmic bias in credit decisioning processes.

Algorithmic bias and transparency: Although existing literature acknowledges the challenges of algorithmic biases in AI deployment, the differentiated ways in which these biases could manifest and affect lending practices requires more robust exploration. This research proposes that more focused empirical studies be conducted to investigate how algorithmic biases impact specific demographic groups in the context of bank lending.

P6 recommended that Bank X adopt a controlled implementation strategy involving AI-assisted recommendations rather than fully automating the process. With this strategy, AI will generate recommendations which the RM will first review and adjust for any biases, through application of critical thinking, before granting final approval. This will ensure fairness and minimises bias, whilst still maintaining the essential human element in decision-making. Banks should continue to refine their AI by training it on customer data and running it through various models until those hallucinations and bias start reducing. Only when they feel confident that AI has been sufficiently trained should they consider full automation and integration into banking processes.

Addressing this gap will not only pave the way for successful adoption but also ensure that the benefits are equitable and widely enjoyed across the banking sector.

5.3 Research objective 2 conclusions

Research objective 2 sought to explore how the role of RMs evolves with the adoption of GenAI and its effect on customer experience. Proposition 2 suggests that GenAI adoption transforms the role of RMs from transaction processors to trusted advisors, significantly enhancing customer experience through personalised and strategic interactions.

5.3.1 Literature findings

Existing literature holds true for proposition 2, with findings acknowledging the potential for GenAI to transform the existing RM role, leading to improved efficiency and personalised and customer-centric interactions. Zegullaj *et al*. (2023) recognised that GenAI adoption in banking would be driven by customer-centricity as the role of the RM evolves. Devan *et al*. (2024) posited that GenAI's ability to analyse large amounts of customer data would enable RMs to provide tailored recommendations to customers.

Kayode (2024) and Hamzah *et al*. (2016) further suggested that AI-powered chatbots and virtual assistants could predict customer needs and manage customer queries, thereby freeing up RMs to have more personalised conversations with customers. Hamzah *et al*. (2016) went on to add that adoption of GenAI would equip RMs with data analytics tools for data-driven customer insights, resulting in enhanced personalised advice to clients.

Empirical evidence and case studies provided by McKinsey (2023), Deloitte (2024), HSBC (White, 2021) and DBS Bank (2023) support the proposition, highlighting RMs ability to provide bespoke advise and tailored solutions to customers through the adoption of GenAI technologies. This shift in role is posited to build stronger customer relationships and drive revenue growth for the bank. The case studies of McKinsey (2023), Deloitte (2024) and Miah (2024) suggested that adoption can augment rather than replace the RM role. A key implication of this proposition is that RMs would require new skills to be able to navigate and leverage an AI driven landscape.

Zegullaj (2023), however, cautioned against over-dependency on AI technology, suggesting this could result in an impersonal customer experience, and stressing the need for balance between automation and the human touch. Oracle (2021) raised added concerns regarding job security and resistance to change, highlighting the need for specialised RM training and change management. The literature suggests that banks should adopt a practical approach by equipping RMs with the correct tools for enablement, whilst still maintaining a personal touch.

5.3.2 Interview findings

Interview findings for Objective 2 support the proposition that GenAI has the potential to automate routine tasks, thereby allowing RMs to focus on relationship-building and strategic advising. Participants consistently recognised that adopting GenAI could lead to significant efficiencies and enable RMs to provide more personalised service offerings to customers.

Transformative potential: Feedback was that GenAI's capability for advanced data analytics could equip RMs with the opportunity for proactive engagement and tailored recommendations to customers. There was, however, notable apprehension regarding the potential for job loss and resistance to change among RMs, driven largely by concerns regarding skills inadequacy and fear of technology.

Need for skills development: Both technical and soft skills are suggested for RMs to navigate the new AI-driven landscape effectively. Notable, is the consensus regarding the need for balance between automation and the human touch, which fosters personalised relationships with clients.

5.3.3 Gaps in the Literature

While the literature acknowledges that GenAI adoption would lead to improved efficiencies and free up RMs for more personalised interactions with customers, there are noted gaps in the findings that are detailed below.

Resistance to technology adoption: Existing literature acknowledges some resistance to GenAI in financial services, though it has not thoroughly examined the sources of this resistance specific to RMs in bank lending. This research addressed the gap through interviews conducted with RMs to uncover the underlying reasons for resistance to change. The findings revealed that RM lack of knowledge about AI systems foster fear of the unknown, which contribute to concerns over job security and thus reluctance to adapt. To mitigate this, the research proposes two targeted training initiatives for RMs: soft skill development focused on empathy and communication, and AI literacy training. These initiatives aim to equip RMs to better navigate the evolving AI-driven landscape.

Role-specific skills development: Existing literature has noticeable gaps regarding tailored upskilling programs for RMs to effectively leverage GenAI technology. Specific competencies needed to maximise AI's potential while maintaining human connection were underrepresented. This research has addressed the gap through targeted interviews with RMs and architects, gathering insights into the precise training needed. From an architecture perspective, P6 stressed the critical need for RMs to receive Prompt Engineering training - crucial for minimising instances of erroneous outputs and 'hallucinations' in AI responses. P6 shared his personal journey with the prescribed training, explaining how it empowered him to successfully integrate and utilise GenAI in his work. This approach highlights that mastering the ability to create effective prompts with high-quality inputs could significantly enhance the relevance and accuracy of AI outputs, thereby reducing the occurrence of hallucinations.

Customer perceptions of AI interactions: While much emphasis has been placed on RM efficiency improvements, there is limited literature addressing the customer's experience and perception of GenAI in banking processes, particularly how customers evaluate automated systems compared to human interactions. This study proposes that empirical research be conducted to capture customer sentiments toward AI integration in banking services. Surveys and feedback mechanisms should be put in place to gather data on client preferences concerning automation and personal interaction. This could lead to refined AI strategies that resonate more effectively with customer expectations.

5.4 Research objective 3 conclusions

Research objective 3 sought to identify opportunities and challenges of integrating GenAI into relationship management within bank lending. Proposition 3 suggested that GenAI adoption in bank lending services presents both opportunities and challenges which must be overcome for successful integration.

5.4.1 Literature findings

The literature of Kayode (2024), Mossavar-Rahmani and Zohuri (2023) and Sharma *et al*. (2023) recognise the potential benefits of GenAI adoption in bank lending to include improved operational efficiencies, product personalisation, cost reductions and enhanced risk and fraud management. It also acknowledges the potential challenges of integration, with Maple *et al*. (2023) and Oracle (2021) identifying data bias and privacy issues, loss of human touch and fear of job loss as being key issues.

Proposition 3 is supported in empirical research conducted, with the study of Devan *et al*. (2024) highlighting proposed benefits of predictive analytics in customer service, personalised banking, credit assessment and operational efficiency. The findings of Bhatore *et al*. (2020) indicate that AI-powered chatbots and virtual assistants could transform customer experience through personalisation and customised lending.

Other case studies supporting this proposition include that of JPMorgan Chase, who implemented a digital tool called COIN - Contract Intelligence, to automate loan agreements (Weiss, 2017). This allowed the bank to process loans in seconds, thus saving the legal department 360,000 hours in processing time and enhancing efficiency, whilst reducing operating costs.

Existing literature also recognised that, despite opportunities for GenAI adoption, there were concerns regarding data biases and ethics. This highlights the need for stringent data protection and governance interventions (Domokos & Sajtos, 2024). The authors have argued that responsible use of AI in bank lending is crucial to mitigate risk and bias in results. The various studies of Dhake *et al*. (2024), Kate *et al* (2020), Maple *et al*. (2023) and Oracle (2021) have proven that AI algorithms inherit biases in data on which they are trained, leading to unfair decision-making in lending approvals and credit evaluations and potentially disadvantaging certain demographic groups. Krijger (2023, p. 221) commented that “AI systems that replicate and exacerbate existing disparities can structurally disadvantaging certain groups”. The literature findings highlight the importance for banks to design and govern high-quality data processes to address AI ethics.

Königstorfer and Thalmann’s study (2020), further reveal a lack of focus on AI applications in commercial banks despite its potential to transform business operations and enhance customer experience. Goldman Sachs’ survey (BCG, 2023), also surfaced concerns around data biases and lack of necessary skills. The author listed data governance and compliance, unbiased data sets, managed AI services and upskilling of resources as some of the strategies for successful integration to overcome challenges (BCG, 2023).

The literature has argued that the benefits of GenAI (Krijger, 2023; Maple *et al.,* 2023) outweigh the challenges (Königstorfer & Thalmann, 2020; Krijger, 2023; Maple *et al.,* 2023), necessitating the importance of interventions for successful adoption and integration.

5.4.2 Interview findings

Interview feedback for Objective 3 align closely with existing literature, with participants recognising the dual aspects of GenAI adoption in bank lending, i.e., its transformative opportunities and inherent challenges.

Opportunities: Findings from interviews align with existing literature, highlighting that GenAI can significantly enhance efficiencies, customer experiences, and personalisation in banking. Participants recognised that the tool could automate routine tasks, thus enabling RMs to focus on more complex client interactions. Furthermore, GenAI's analytical capabilities could lead to better decision-making and risk management.

Challenges: Respondents noted that the integration of GenAI is not without obstacles. Significant challenges identified, include data quality and bias issues, the risk of job loss, and the potential loss of the human touch in customer relationships.

Strategies for successful integration: To address the above challenges, participants proposed several interventions: the establishment of robust data management strategies, effective governance and regulatory frameworks, adoption of hybrid models balancing AI efficiency with human oversight, and provision of effective training and change management.

5.4.3 Gaps in the Literature

Whilst the literature acknowledges both the opportunities and challenges of GenAI adoption in relationship management, there are noted gaps in the findings that are detailed below.

Balancing automation and the human touch: Existing literature paints a one-dimensional view of technology replacing human roles. It lacks in-depth discussions about maintaining the human element in customer relationships amidst increased automation efforts. It is still unclear as to how RMs perceive GenAI in their workflows, particularly concerning psychological factors like trust and job security This research proposes a hybrid operating model that incorporates both GenAI capabilities and human intervention in customer interactions. P6 suggested a *recommendation* approach where AI would recommend a decision over full automation. The RM will then oversee the recommendation, reviewing and adjusting any biases by applying critical thinking, before granting final approval. This approach would not only ensure unbiased decision-making, but additionally, still maintain the human touch. This is a highly effective approach to balancing AI automation and RM interaction for optimum customer experience.

Culturally inclusive AI practices: Current literature appeared dominated by Western perspectives, particularly regarding biases in AI algorithms. There is a gap in understanding how cultural nuances influence the perception and effectiveness of GenAI in different market contexts. This research suggests cross-cultural studies to explore how different cultural contexts shape the development and acceptance of the technology. This could involve comparative case studies of banks in diverse global markets to understand regional challenges and solutions.

Training and change management: The literature predominantly focuses on theoretical frameworks and potential benefits without adequately addressing the practical factors that hinder implementation, such as RM resistance to change and the need for significant upskilling to embrace digital adoption. This research suggests the development of comprehensive frameworks that outline best practices for implementation, including change management strategies and addressing resistance to technology adoption among RMs. Sharing success stories and equipping leaders with tools to foster a supportive environment at all organisational levels can also foster smoother transitions to new technologies.

Frameworks for ethical AI reporting: While some frameworks for governance exist, comprehensive, industry-wide guidelines that detail ethical AI reporting practices specifically for banks, remains limited. More research is needed to establish best practices. This study suggests establishment of a governance and regulatory framework tailored to the banking sector, with specific guardrails around the ethical use of AI. Included should be guidelines on data privacy, algorithm auditing, and ensuring transparency in AI-driven decision-making. P3 proposed a formalised division dedicated to GenAI, seeing as adoption is rapidly growing in financial services. Bringing together experts in the fields of AI ethics, sociology, banking, and data science could yield a broader understanding of the implications of AI adoption in banking, leading to well-rounded strategical approaches. This would help manage risk and set expectations for the use of the technology.

Addressing these gaps in knowledge will allow banks to better embrace GenAI, fostering an environment that balances technological efficiency with ethical responsibility. This will ultimately enhance customer and employee satisfaction.

5.5 Recommendations

In a rapidly evolving digital banking landscape, customer experience has become a crucial element in building loyalty and promoting growth, particularly in bank lending. As financial institutions increasingly seek innovative solutions to meet the diverse needs of their customers, GenAI adoption by RMs emerges as a transformative opportunity. Realising the full benefits of GenAI necessitates a collaborative effort among key stakeholders. To successfully navigate this journey, it is essential to implement targeted recommendations tailored to each group. Drawing from comprehensive research findings, this study presents the following recommendations for enhancing customer experience in bank lending through strategic actions and partnerships among banks, RMs, customers and policymakers.

5.5.1 Recommendations for banks

5.5.1.1 Training program design

In an era where GenAI is transforming traditional banking processes, RMs must be equipped with both technical and interpersonal skills, as technology alone cannot drive customer satisfaction; the human element is crucial. This dual approach will empower RMs to navigate the new AI-driven landscape effectively.

Banks should implement tailored training programs to maximise the impact of GenAI on their RMs' ability to provide enhanced customer experiences in lending.

GenAI literacy and understanding

Ensure RMs understand the capabilities and limitations of GenAI. This can be facilitated through workshops on GenAI basics, including how it works (e.g., natural language processing, predictive analytics). Case studies of other banks successful implementations can also be reviewed and critiqued. This can take the form of interactive workshops with practical examples and hands-on sessions.

Enhanced customer engagement techniques

Equip RMs with skills to leverage GenAI for personalised customer experiences. Data insights can be used for customer profiling and segmentation. RMs should be provided with Interactive training on responding to customer inquiries using GenAI tools. As an example, scenarios can be role-played where RMs use chatbots or virtual assistants to assist customers.

Data-driven decision making

RMs should be provided with training on how to act upon, and analyse customer data, through leverage of insights provided by GenAI. Workshops should be conducted on how to leverage data analytics to identify customer needs and preferences, thus translating data analytics into actionable strategies for enhancing customer relations. This can inform how GenAI is deployed in lending processes and could be in the form of hands-on activities with data analysis tools and live demos. Insights from data should be used to adapt strategies and offerings continuously, ensuring they remain relevant and effective.

Talent acquisition and Training

Banks should invest in hiring or training personnel with expertise in AI, machine learning, data analytics and user experience design, ensuring that teams are well-equipped to leverage GenAI effectively. They should encourage collaboration across departments such as IT, risk management, data analytics, and customer service to foster a holistic approach towards GenAI implementation.

Culture of continuous learning

Banks should foster a culture of continuous learning to help employees adapt to and embrace new GenAI technologies. Innovation should be encouraged whilst ensuring that employees recognise their responsibility in managing risks associated with AI technologies.

5.5.1.2 Technical infrastructure needs

Banks should invest in robust technical infrastructure if they wish to effectively harness the transformative potential of GenAI to enhance customer experiences in lending and beyond. The goal should be to create a flexible, secure, and customer-oriented ecosystem that, not only meets current demands, but also anticipates future needs in the dynamic digital banking landscape.

Cloud based scalable AI platforms

Banks should invest in robust, scalable AI platforms that can handle increasing data volumes and user interactions effectively. This could include cloud-based solutions that offer flexibility and increased computational power. Cloud services can provide the necessary scaled computational power required for GenAI applications. Recommendation would be for a hybrid cloud strategy to optimise costs and ensure data sovereignty, making it easier to manage sensitive financial data while leveraging public cloud capabilities.

Data management framework

Banks should establish AI driven data governance frameworks to ensure the necessary adherence to accuracy, security and compliance of data utilised by GenAI models, to reduce biases in algorithms. A dedicated data governance team should be established to monitor, manage and improve AI-driven data processes, focusing on bias detection and remediation protocols. This includes establishing processes for regular auditing of AI decision-making frameworks to improve transparency and accountability, as well as transparent frameworks for customers, outlining how their data will be used. This will ensure compliance with privacy regulations and building trust in AI systems. Banks should also consider a centralised and secure data repository that integrates various data sources, such as customer interactions, transaction histories, and credit assessments. This would ensure that GenAI can access comprehensive datasets for better insights. Mechanisms to regularly update and validate AI models, in light of new data and societal changes, should be implemented.

AI and machine learning capabilities

Banks should invest in the development or integration of advanced machine learning engines that can efficiently train and fine-tune GenAI models based on real-time data inputs. This should include processes for continuous monitoring, evaluation, and retraining of models to adapt to changing customer behaviours and market conditions.

Interoperability and integration

Banks should invest in an API strategy that allows seamless integration between legacy systems and new GenAI applications. This would help in maintaining operational continuity while enhancing capabilities. Consideration should be given to adopting microservices architecture to allow different components of the banking system to interact efficiently and independently, thus facilitating agile development and deployment of GenAI solutions.

User experience and interface design

The design of user-friendly interfaces that facilitate easy interaction with GenAI features should be a key consideration. This may involve intuitive chatbots for customer inquiries or simplified loan application processes. Banks should incorporate feedback loops to understand user experience, and improve the GenAI applications continually, based on user behaviour and preferences.

5.5.1.3 Invest in change management strategies

Establishment of effective change management strategies are vital for successful implementation and adoption of GenAI within banks to maximise its benefits and should include the following:

Clear vision and objectives

Banks should define the specific goals aimed to be achieved with GenAI adoption, such as improved customer experience, streamlined operations, better risk assessment, or personalised lending solutions. This vision should be communicated to all stakeholders, ensuring alignment and understanding of how GenAI can transform their roles and the bank's services.

Leadership engagement

Senior leadership should be engaged in change management initiatives to champion the adoption of GenAI. A chief transformation officer or a dedicated task force should be appointed to champion the GenAI initiative. Leaders must articulate a compelling vision for using GenAI aligned with the bank's overall goals, emphasising how it will enhance customer experience and empower RMs. This will ensure ongoing executive support which can build confidence and encourage organisational buy-in.

Early stakeholder engagement

All relevant stakeholders - management, risk teams, IT, operations, and RMs, should be included in the planning and implementation phases. Input and feedback should be gathered from these groups to understand their concerns and expectations regarding GenAI utilisation.

Culture of innovation

Banks should encourage an innovation mindset within the organisation that embraces change and experimentation. Employees who contribute to the successful integration of GenAI, and demonstrate innovative uses of technology in their roles, should be recognised and rewarded. Banks could also consider offering a 'change ambassador' program where selected RMs act as champions of AI adoption by sharing experiences and assisting peers, building a supportive community.

Cross-functional teams

Interdisciplinary teams should be formed that include members from technology, compliance, customer service, and lending. These teams can oversee the implementation process, ensuring comprehensive coverage of all aspects affected by GenAI. Collaboration and knowledge sharing should be encouraged amongst departments to break down silos.

Customer-centric solutions

Banks should prioritise initiatives that enhance customer experience through GenAI, such as personalised loan offerings, chatbot assistance, and streamlined application processes. Feedback should be requested from customers to regularly refine AI-driven services and ensure they meet client expectations.

Pilot programs and iterative development

GenAI applications should be piloted in controlled environments, allowing for adjustments based on performance and user feedback before full-scale implementation. These pilots should be used to demonstrate value and build confidence among stakeholders. Furthermore, focus should be on adoption of agile methodologies in software development for iterative improvements based on ongoing feedback and changing customer needs.

Feedback loop and continuous improvement process

Robust feedback mechanisms should be implemented to allow customers and employees to provide input on GenAI outputs and overall experience. This could be in the form of an easy-to-use feedback platform or app for RMs and customers to share their experiences and suggestions regarding GenAI tools in real-time. This feedback should be used to iteratively improve AI algorithms and enhance service delivery, ensuring alignment with customer needs and expectations.

Monitor and evaluate progress

Banks should establish metrics to evaluate the effectiveness of GenAI initiatives through implementation of robust feedback systems. They should monitor and assess the adaptation process through surveys and informal meetings, encouraging open discussions around challenges and successes. This can be used to gather insights from both RMs and customers on their interactions with GenAI tools. Banks can use this data to iterate and improve AI systems continually.

Balance automation with the human touch

Banks should design a hybrid operating model in bank lending that incorporates both GenAI capabilities and human intervention in customer interactions. Policies should be created that require RMs to apply their human skills in high-value engagements, especially for complex or sensitive customer situations. Customer journey maps should be created that identify points where human interaction adds value, such as first-time borrowers or customers with complex financial situations. This will serve to reinforce the roles of RMs where empathy and understanding are critical. Workshops should be staged where RMs can practice scenarios that require balancing efficiency through GenAI with personal customer engagement, nurturing both skill sets.

5.5.1.4 Risk implementation approaches

The adoption of GenAI technologies into banks brings with it multiple benefits but also introduces new risks which must be managed effectively. Banks can mitigate risks by putting in place risk implementation and mitigation strategies.

Robust governance framework

Banks should establish comprehensive frameworks encompassing policies, procedures and oversight mechanisms that govern the use of GenAI. A cross-functional steering committee should be set up that includes compliance, risk management, IT and operational teams to oversee GenAI initiatives. Part of the governance should be an ethical AI framework that emphasises transparency, fairness and accountability in AI-driven decision-making, mitigating the risk of bias and ensuring compliance with regulations.

Risk assessment and mitigation

Regular risk assessments should be conducted to identify potential risks associated with GenAI applications, including data privacy, model bias, and operational risks. Banks should implement risk mitigation strategies based on the identified risks, ensuring that there are controls and safeguards in place. Contingency plans should be established to address possible failures or negative consequences of AI deployment, ensuring that there are fallback mechanisms in place to protect customer interests.

Security and compliance

Focus should be given to implementing strict cybersecurity measures to protect sensitive customer data from breaches and unauthorised access when deploying GenAI technologies. Banks should also keep abreast of regulatory requirements related to data usage, privacy and AI technologies. Implementing compliance checks into the GenAI workflows is crucial to avoid legal and audit breaches.

Transparent communication

Banks should maintain transparent communication with customers regarding the use of GenAI, including how their data will be used and the benefits of AI-driven lending solutions. Customers will need to be educated on AI decision-making processes to build trust and ensure they feel comfortable engaging with AI-driven services.

Third-party risk management:

Thorough due diligence should be conducted on third-party vendors who provide GenAI solutions, assessing their compliance with industry standards and regulatory requirements. Clear contracts should be established outlining data ownership, liability and accountability measures related to AI solutions.

Scenario analysis and stress testing

Scenario analyses and stress testing should be conducted on GenAI-based decision-making processes to understand potential vulnerabilities and impacts under various conditions. These insights should be used to reinforce risk management strategies and prepare for adverse conditions.

Regulatory compliance and engagement

Banks should stay informed and compliant with changing regulations related to AI and data usage in lending and banking. They should proactively engage with regulators to contribute to the development of frameworks and standards governing the use of AI in the banking sector.

5.5.2 Recommendations for RMs

5.5.2.1 Skills development priorities

As the role of RMs continues to evolve, those who balance technological proficiency with strong interpersonal skills will undoubtedly lead the way in fostering customer engagement and loyalty in the bank lending process.

Understanding of GenAI technologies

RMs should have a basic understanding of how GenAI works, including concepts such as NLP and predictive analytics. A level of data literacy is also required to be able to understand and analyse data generated by AI tools. This includes familiarity with data sources, interpretation of analytics, and how to apply insights in customer interactions.

Customer-centric mindset

RMs should develop an understanding of customer journeys and adopt GenAI tools to gather customer insights and preferences to provide personalised offerings. They should leverage AI generated automated suggestions to enhance their advisory roles and build stronger client relationships.

Technology proficiency

RMs should develop skills to effectively use specific GenAI applications such as automated scheduling, chatbots for initial inquiries, and customer analytics dashboards. With an increase in digital interactions and cybersecurity, RMs should prioritise understanding data privacy and security protocols to protect customer information.

Communication and collaboration skills

Effective communication is vital, especially when conveying complex AI-generated insights to customers. Collaboration with data scientists and tech teams is also fundamental for effective adoption of the technology.

Adaptability and continuous learning

RMs should imbibe a growth mindset and foster a habit of continuous learning to keep pace with evolving GenAI technologies and changes in the digital banking landscape. They should stay abreast of industry trends and advancements in GenAI and digital banking through webinars, industry reports, and workshops.

Ethical considerations

RMs should be proactive in promoting fairness and accountability within AI-driven processes. They should be educated on ethical considerations surrounding AI in lending practices and act as a bridge between technology and customer satisfaction in understanding the nuances of AI algorithms and advocating for ethical practices.

5.5.2.2 Adaptation strategies

Below are potential adaptation strategies that RMs could adopt to allow them to effectively leverage GenAI. By embracing these strategies, RMs can create a more robust banking experience for their customers and position themselves as trusted advisors.

Integrate GenAI in customer interactions

RMs should utilise GenAI tools to analyse customer data and provide personalised recommendations tailored to individual borrowing needs. Through AI-generated insights, RMs will have the ability to proactively anticipate customer needs and reach out with suitable offerings or advice, thereby providing an elevated level of service.

Data-driven decision-making

RMs should leverage AI-driven analytics to assess creditworthiness, risk factors and lending trends, enabling more informed decision-making. GenAI should be used to gather customer insights and synthesise feedback, thus allowing RMs to better understand customer preferences and pain points.

Foster collaboration with tech teams

RMs should work closely with data scientists and tech teams to share customer insights that can inform AI model development. Feedback loops should be established to report back on the effectiveness of AI tools, ensuring they evolve based on real-world application.

Enhance customer education and awareness

Customers should be provided with educational resources that explain how AI is being used to improve their banking experience, thus building trust and understanding. Workshops and seminars should be organised to explain new lending products or services powered by GenAI, fostering a deeper connection with clients.

Measure impact and adjust strategies

Key performance indicators (KPIs) should be established to measure the effectiveness of GenAI initiatives in customer engagement and lending outcomes. An iterative approach should be used to regularly assess the impact of AI tools and adjust strategies based on performance data and customer feedback.

5.5.2.3 Career development paths

The following recommendations outline strategic career development paths that RMs can pursue to leverage GenAI effectively, collaborate with cross-functional teams and ultimately position themselves as leaders in the digital banking revolution. By focusing on these key areas, RMs can enhance their capabilities, remain competitive and drive customer loyalty through innovative, technology-driven solutions.

Enhance digital literacy

RMs should invest time in learning about digital banking tools, AI applications, and fintech innovations. Familiarity with GenAI will empower RMs to leverage technology effectively in their interactions with clients and enhance service delivery.

RM emotional intelligence:

As technology evolves, the human element of banking remains crucial. RMs should enhance their skills in emotional intelligence to better understand client needs and build trust. When clients feel heard and understood, they are more likely to trust their RMs with their financial needs and concerns. This understanding goes beyond surface-level transactions, enabling RMs to provide tailored solutions that genuinely align with clients' needs. This skill not only allows them to understand clients better but also to foster trust and build long-term relationships, ensuring that the human element of banking thrives amidst technological advancement.

Career pathways and mentorship

Roles focussing on digital strategy, customer experience management or technology partnerships should be considered by RMs as these may provide opportunities to leverage GenAI more directly. They should seek mentorship from experienced professionals in digital banking or AI. Developing leadership skills will prepare RMs for managerial roles in the future.

Industry networking

RMs should join professional associations or attend industry conferences related to digital banking and AI. Networking can offer insights into trends and opportunities for career advancement.

Build a personal brand

Social media and professional platforms should be leveraged to share insights on customer experience and technology in banking. Building a personal brand can establish RMs as thought leaders in the industry.

5.5.3 Recommendations for customers

Engage with the bank

Customers should be encouraged to actively communicate their expectations regarding AI's role in their banking experience. This open dialogue can be facilitated through surveys, focus groups, or dedicated feedback channels where customers can share their thoughts and concerns. By providing feedback on AI-driven interactions, customers can help banks refine their GenAI offerings, ensuring that these technologies align more closely with client needs and preferences. This collaboration not only improves the banking experience but also fosters a sense of partnership between customers and their financial institutions.

AI education

Customers can greatly benefit from a better understanding of how GenAI impacts their borrowing experiences and banking transactions overall. To achieve this, banks should provide accessible and straightforward resources that explain how GenAI works and its role in lending processes. These resources could include articles, webinars, or interactive tutorials that demystify AI concepts and clarify how these technologies can facilitate faster loan approvals, personalised service offerings, and improved financial decision-making. By enhancing customers' knowledge of GenAI, banks can build trust and empower clients to make informed choices about their financial futures.

Request human interaction

Customers should express their preferences for personalised advice and complex queries in need, to ensure that RMs remain integral to their experience. They should be vocal in advocating for a hybrid approach in maintaining human interaction where necessary. This proactive communication will not only enhance the customer experience but also reinforce the value of personal connections in an increasingly automated financial landscape.

5.5.4 Recommendations for policymakers

Develop regulatory frameworks for AI in banking

Policymakers should formulate comprehensive policies governing the ethical use of GenAI in banking. This would ensure that data privacy, reduced bias, and maintained transparency in AI-driven decision-making processes is always at the forefront of considerations for ethical use of AI. They should further facilitate partnerships between financial institutions and technology experts to develop best practices in AI integration while ensuring the ethical implications are thoroughly considered.

Encourage research on algorithmic bias

Policymakers and regulatory bodies should actively encourage and fund comprehensive research studies that delve into the far-reaching implications of AI biases, particularly in the context of diverse demographic profiling in the financial sector. This research is crucial in helping to identify and address biases that can disproportionately affect marginalised communities and undermine fairness in lending practices. By examining the intricate relationship between AI-driven decision-making and diverse demographic profiles, policymakers can develop a deeper understanding of the root causes of biases and create targeted strategies to mitigate their effects.

Support workforce development

Policymakers should invest in educational initiatives aimed at equipping RMs and the greater workforce with the necessary skills to thrive in an AI-driven environment. This could involve partnerships with educational institutions to create relevant curriculums that emphasise AI literacy, data analysis, and critical thinking. Policymakers could also consider funding programs that provide professional development opportunities, such as boot camps, workshops, and online courses, to help RMs and their peers build the skills and confidence needed to work effectively with AI systems.

5.5.5 Overall strategic recommendation

The overall recommendation is for banks to create a collaborative ecosystem that includes a cross-sector coalition of banks, RMs, technology providers and consumer advocates. This establishment should focus on sharing best practices, developing industry standards, and addressing common challenges associated with the integration of GenAI

By adopting these recommendations, stakeholders can work together to ensure that the integration of GenAI enhances customer experiences in bank lending while addressing concerns related to ethics, bias, and the evolving role of RMs.

5.6 Theoretical contributions

The findings that emerged from this research study have provided new insights into the adoption of GenAI in the banking sector that enrich and extend the constructs of the UTAUT2 framework. The study introduces new theoretical perspectives, particularly around ethical AI, the evolving role of RMs and the importance of cultural and governance factors. Additionally, the research proposes modifications to the UTAUT2 framework to better capture the complexities of AI adoption, providing a comprehensive basis for future theoretical developments in technology acceptance.

5.6.1 How findings extend UTAUT2

The research findings in this study relate to the existing elements of the UTAUT2 framework and have also identified potential areas of expansion as detailed below:

Performance Expectancy: The analysis indicates that GenAI can enhance the efficiency of credit lending processes and improve product personalisation. By demonstrating the positive impact GenAI has on improving operational efficiency (increased processing speed, reduced manual tasks) and customer experience (tailored recommendations), the findings reinforce and extend the concept of performance expectancy within UTAUT2. Additionally, the identification of gaps in empirical evidence regarding algorithmic bias highlight the need for a deeper investigation into how perceived performance may be influenced by the fairness and transparency of AI technologies.

Effort Expectancy: Findings regarding the evolving role of RMs also illustrate the notion of effort expectancy. The interviews highlight that while GenAI adoption frees RMs from routine tasks, allowing them to focus on strategic relationship-building, there are concerns about the learning curve associated with new technologies. Existing literature on the resistance to technology adoption emphasised this gap in understanding the perceived effort required for successful integration. The study suggests that targeted training and development for RMs (both technical and soft skills) is crucial for reducing effort expectancy barriers.

Social Influence*:* The study reveals the critical role of social influence in the adoption of GenAI, particularly concerning resistance from RMs due to job security fears and the need for cultural acceptance of AI technologies. By exploring interpersonal dynamics and resistance to change, the findings extend the social influence component of UTAUT2, offering insights into how the perceptions of peers and leaders within organisations impact the acceptance of GenAI.

Facilitating Conditions*:* The research contributes to the understanding of facilitating conditions by pinpointing practical challenges related to integrating GenAI into existing RM workflows. Issues such as data quality, bias, and the necessity for a robust governance framework highlight the environmental conditions required for effective technology adoption. The research advocates for structured change management and governance protocols as essential facilitating conditions that are perhaps underspecified in the UTAUT2 framework.

Hedonic Motivation and Price Value*:* The research recognises that RMs' intrinsic motivation, driven by factors such as job satisfaction, and the sense of mastery associated with leveraging advanced AI technologies, plays a vital role in their willingness to integrate GenAI into their workflows. When RMs find working with GenAI engaging, rewarding, and aligned with their professional aspirations, they are more likely to embrace its use and actively promote its benefits in their interactions with clients. Moreover, fostering a positive experience with GenAI can enhance RMs' job satisfaction, reduce resistance to change, and motivate continuous learning and adaptation. Recognising this, the study recommends creating an environment where RMs perceive the use of GenAI not just as a tool for efficiency but also as an engaging and fulfilling aspect of their roles. This intrinsic motivation can ultimately lead to more effective adoption, better support for customers, and improved customer service outcomes, which ultimately will lead to increased revenue generation for the bank.

5.6.1.1 *Suggested extensions to UTAUT2*

Algorithmic fairness: Introduce a dimension within UTAUT2 that addresses algorithmic bias and fairness in technology acceptance, emphasising transparency and user trust in AI-driven systems.

Cultural nuances: Propose an inclusion of cultural aspects in understanding technology adoption, encouraging studies that explore the diverse expectations and perceptions surrounding AI in different demographic and geographic contexts.

Human-AI interaction: Expand the framework to incorporate the nuanced dynamics of human-AI interaction in technology acceptance to emphasise maintaining the human element amidst increased automation.

Skills development frameworks*:* Integrate the concept of skill enhancement as a category that impacts effort expectancy and performance expectancy, proposing that organisations implement comprehensive training programs to facilitate technology adoption.

Governance and ethical practices*:* Establish guidelines around ethical AI practices as structural facilitating conditions essential for technology acceptance in sensitive domains such as banking.

This study's findings suggest a rich basis for extending the UTAUT2 framework, illustrating a multifaceted approach to understanding technology adoption amidst challenges and opportunities presented by GenAI in the banking sector. It not only contributes to academic literature, but also offers practical recommendations for stakeholders in the financial industry.

5.6.2 New theoretical insights

Several theoretical insights can be garnered from the research conducted and its associated findings. These insights surface the broader implications of GenAI integration, the evolution of RMs, and the challenges associated with technology adoption as follows:

Transformational role of AI in bank relationship management

The findings indicate a substantial shift in the role of RMs from traditional transaction processors to strategic advisors. This shift supports the theory of role evolution in response to technological advancements. The dual aspects of AI enhancing efficiencies while simultaneously requiring new skill sets establish a framework for understanding how professionals adapt to rapidly evolving technology.

Human-AI collaboration framework

The proposed hybrid operating model, which emphasises a balance between GenAI capabilities and human oversight, contributes to the emerging theory of collaborative intelligence in banking. This concept advocates for a synergistic relationship where RMs' critical thinking complements AI's data-driven insights. This proposes that successful AI deployment is not about replacement but augmentation, reinforcing the value of human expertise.

Algorithmic bias and ethical AI frameworks

The identification of algorithmic bias presents a significant theoretical contribution to the field of AI ethics. By highlighting the need for more granular research into the manifestations of biases in AI decision-making, this study calls for a nuanced understanding of intersectionality in AI ethics - specifically how demographic variables interact to shape the impact of AI systems on decision processes. This opens the door for developing frameworks that ensure fairness and equity in AI-enhanced banking services.

Change management and employee resistance frameworks

The findings emphasise the importance of change management theories focusing on technology adoption, particularly regarding employee resistance. The identification of fears related to job security, AI literacy, and the psychological impacts of technology on RMs signals a potential refinement of existing models. This could lead to the development of targeted training and support systems that address. not only the practical skills needed, but also emotional and psychological readiness for change.

Customer experience and AI perception studies

The call for empirical research into customer perceptions of AI interactions invites the expansion of the customer experience (CX) theory to incorporate AI components. This suggests a re-evaluation of what constitutes customer satisfaction, loyalty, and trust in automated environments. It could envision a new dimension of CX theory that integrates user experience with AI interactions, focusing on how these experiences shape customer attitudes.

Governance and ethical standards for AI

The proposal for governance frameworks specific to AI in banking leads to insights into the systemic implications of AI use. Theoretical advancements in organisational behaviour and ethical responsibility can emerge from this need for structured compliance and accountability in AI operations, advocating for an integrated approach to governance that aligns with broader industry standards.

The research findings provide great consideration for theoretical advancements. Future research can build upon these insights, leading to more comprehensive theoretical models that embrace the complexities of advancing technology in traditional sectors like banking.

5.6.3 Framework modifications

Given the evolving banking landscape brought about by GenAI and the insights provided above, several modifications to the UTAUT2 framework can be recommended which will serve to refine the framework to better capture the unique factors at play in banking.

Addition of collaborative intelligence construct

Introduce a new construct that focuses on the acceptance of collaborative intelligence, where employees perceive AI as a partner rather than a replacement. The rationale here is that it aligns with the Human-AI Collaboration Framework, emphasising the synergy between RMs and AI, enhancing not only RMs' effectiveness but also their perceived value.

Incorporation of ethical and bias awareness

Integrate a construct related to ethical AI awareness and the perception of algorithmic bias. This adjustment would help assess how concerns regarding equity and fairness affect technology adoption.

Expanded change management considerations

Enhance the existing Facilitating Conditions construct to include psychological readiness and emotional support systems as integral to technology acceptance. This reflects the Change Management and Employee Resistance Framework and acknowledges that preparing employees emotionally and psychologically can significantly enhance technology adoption rates.

Customer experience dimensions

Modify the Hedonic Motivation and Price Value constructs to encompass AI interaction components that specifically address customer experiences. By drawing on the insights around customer experience and AI perception studies, this modification would incorporate dimensions of trust, satisfaction and loyalty that stem specifically from AI interactions.

Governance and compliance inclusion

Add a construct related to governance and ethical standards specific to AI use in banking. Given the identified need for governance frameworks, this would help assess institutional support and compliance as motivational factors for both employees and customers regarding AI adoption.

Skill development and AI literacy

Include a construct related to perceived skill development opportunities and AI literacy as factors influencing acceptance. This will support the findings indication of technological advancements necessitating new skill sets. Understanding how perceived opportunities for skill enhancement influences acceptance can garner better insights.

The modifications suggested to the UTAUT2 framework by this research study can serve to extend its theoretical applicability to better reflect the complexities introduced by GenAI in relationship management and customer experiences in banking. This will not only enrich the existing framework but also offer more specific pathways for future research, addressing the multifaceted impact of AI within traditional sectors.

Table 9 is an updated version of Table 2, which was introduced in Chapter 2, prior to the surfacing of the research findings. It now includes *Collaborative Intelligence* and *Ethical Governance,* discussed above, as new constructs to the framework. It also includes the prescribed extensions to the existing constructs, such as *Skills development, Governance, Change Management, Ethical practices* and *Hybrid models* that emerged from the research findings. The changes are highlighted in green.

Constructs	Proposition 1	Proposition 2	Proposition 3
Performance Expectancy	• Enhance credit lending processes • Product personalisation	• Personalised and strategic interactions • Transforming role of RM • **Skills development**	• Opportunities – Credit assessments • Opportunities – Customer service • Opportunities – Operational efficiencies • Opportunities – Predictive analytics
Effort Expectancy		• Transforming role of RM • **Skills development**	• Challenges – RM lack of skills • Challenges - Integration
Social Influence	• Customer experience	• Customer experience	
Facilitating Conditions	• **Governance**	• **Change management**	• Challenges – Data bias • Challenges -Upskilling RMs
Hedonic Motivation	• Customer experience	• Customer experience	
Price Value	• Operational efficiencies, Revenue growth		• Operational efficiencies • Revenue growth
Habit			
Collaborative intelligence		• **Hybrid model – Human/AI interaction**	**Hybrid model – Human/AI interaction**
Ethical governance	• **Ethical practices** • **Cultural nuances** • **Governance**		**Ethical practices** **Governance**

Table 9: Proposed framework modifications

Source: Author's own

5.7 Suggestions for further research

As the learnings of GenAI deepens regarding its impact on RM roles and customer experience in bank lending, this research has surfaced important insights and opened opportunities for future studies. While the study looked at many factors affecting how GenAI changes RM roles and customer experiences, it also posed many additional questions. The findings highlight important issues such as the ethical use of GenAI and how RM roles are changing, which suggests further study. The research suggestions that follow, aim to build on what was learnt and address the unanswered questions from this study. By following these suggestions, researchers can explore further, how GenAI affects RMs and customer experiences, leading to new insights in this field.

Algorithmic bias and demographic studies

Conduct research that focuses on the effects of algorithmic bias in GenAI on lending decisions, particularly as they pertain to diverse demographic groups within South Africa. This can include qualitative studies that explore the lived experiences of individuals who have faced biases in credit scores and loan approval processes.

Longitudinal studies on RM roles

Undertake longitudinal studies that track the evolution of RM roles over time in response to GenAI implementation. Empirical studies should focus on the interactions between RMs and GenAI systems to explore how these relationships evolve over the years as technology changes, the trust-building processes and insights into long-term impacts. This will allow for exploration on the best practices for balance between automated services and personal interactions.

Balancing automation and the human touch

Explore the psychological and emotional aspects of the RM's relationship with GenAI systems. Research can investigate how trust is built between RMs and AI, and how emotions influence RMs' willingness to embrace AI tools. This study would contribute practical insights on achieving an effective hybrid operating model.

Customer sentiment analysis

Conduct surveys or focus groups specifically designed to gauge customer perceptions of GenAI technologies in banking. This research could delve into customer acceptance of automated versus human interactions, identifying scenarios where customers prefer human oversight and personalised service over full automation.

Cultural dimensions of GenAI acceptance

Investigate how cultural factors influence the acceptance and implementation of GenAI in banking. Comparative case studies in different regions, particularly in African and non-Western contexts, can provide valuable insights into how societal norms and values affect perceptions of technology in banking services and influence biases.

Framework development for ethical AI practices

Build upon the need for formalised guidelines by developing frameworks for ethical AI governance in banking. This could include best practices for transparency, fairness, and accountability in AI-driven lending processes, drawing on interdisciplinary perspectives to ensure comprehensive coverage.

Change management and RM adaptation

Investigate the change management strategies that banks can implement to facilitate the successful integration of GenAI into RM workflows. This research could explore the role of leadership and organisational culture in supporting RMs transition through AI adoption, emphasising models that alleviate fears of job loss.

Hybrid service models

Research the effectiveness of hybrid service models that combine GenAI tools with RMs. This can involve developing specific case studies of banks that successfully implement such models and quantifying their effects on customer satisfaction, operational efficiency, and RM job satisfaction.

Impact of GenAI on financial inclusion

Investigate how GenAI could influence financial inclusion within under-served communities in South Africa. Research can explore if, and how, GenAI tools mitigate barriers to access and provide equitable lending opportunities for marginalised groups.

These suggestions aim to create a foundation for ongoing research in the evolving landscape of bank lending relationship management enhanced by GenAI technology. By addressing broader cultural contexts, psychological factors, ethical governance and specific training needs, future studies can contribute to a more nuanced understanding of how GenAI reshapes both RM roles and customer experiences in banking.

5.8 Conclusion

The rapid advancement of digital transformation, particularly with the rise of GenAI, combined with the growing pressure for banks to remain relevant in an increasingly competitive landscape, has compelled them to innovate and reassess their service offerings comprehensively. This research explored the impact of GenAI on RM's ability to provide a better lending customer experience.

Conducted through qualitative interviews and thematic analysis, the study affirmed the importance of digital technology - specifically GenAI - in enhancing customer experience and driving organisational growth. The findings of this study set out to provide an in-depth understanding of GenAI adoption, laying a solid foundation for banks to formulate effective strategies for the successful integration by RMs in bank lending.

Key insights from the research indicate that GenAI not only improves operational efficiencies but also fosters greater product personalisation and significantly enhances the overall customer experience, all while transforming the essential role of the RM. The study proposed a conceptual framework utilising the UTAUT2 theoretical model, which offers a structured approach to understand GenAI's transformative role in enhancing bank lending customer experiences. Additionally, it suggests targeted interventions to address the challenges that may arise during adoption.

Ultimately, this study contributes valuable insights to the currently limited literature on GenAI adoption in bank lending, underscoring its growing significance in a highly competitive market. It calls for researchers and practitioners alike to acknowledge and actively address the determinants of successful GenAI adoption. As the banking industry continues to evolve, embracing these findings may empower financial institutions, and in particular, bank lending divisions, to not only elevate customer experiences but also position themselves as leaders in innovation, resilience and service excellence in an ever-changing digital landscape.

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APPENDIX

Appendix A1 - Instrument (Interview Guide for IT Architect)

Standard Participant Questions

1. Please state your role at Bank X.
2. What is your job level in the organisation?
3. How many years have you worked in Bank X?
4. What is the division and functional area that you work in?
5. Have you ever been involved in the development of an Artificial intelligence (AI) strategy at Bank X?

Current role that AI plays

1. Can you explain your understanding of generative AI (GenAI) technology in the context of banking?
2. To what extent is generative AI currently being used at your bank? Can you provide specific examples or use cases?
3. What do you believe are the main advantages and disadvantages of using generative AI in banking operations?

AI and relationship management in bank lending

1. What do you see as the key drivers for implementing generative AI in the bank lending process?
2. In what specific ways do you think generative AI can improve operational efficiency for relationship managers in bank lending?
3. How do you anticipate relationship managers will adapt to the integration of generative AI into their roles? What kind of training or support might they need?
4. In your opinion, what are the primary opportunities and challenges of integrating generative AI into relationship management within bank lending services?

AI and customer experience

1. How do you think integrating generative AI into relationship management practices will impact the customer experience in bank lending? Can you provide potential positive and negative outcomes?

Further insights

1. How do you think the use of generative AI in relationship management will impact customer trust and loyalty?
2. What strategies do you think are necessary to overcome the challenges associated with integrating generative AI into relationship management in bank lending?
3. What specific training or support do you think relationship managers will need to effectively integrate generative AI into their roles?
4. Are there any additional insights or recommendations you would like to share regarding the use of generative AI in bank lending services? What future trends do you foresee in this area?

Appendix A2 - Instrument (Interview Guide for RMs)

Standard Participant Questions

1. Please state your role at Bank X.
2. What is your job level in the organisation?
3. How many years have you worked in Bank X?
4. What is the division and functional area that you work in?
5. Have you ever been involved in the development of an Artificial intelligence (AI) strategy at Bank X?

Current role that AI plays

1. Can you explain your understanding of generative AI (GenAI) technology in the context of banking?
2. To what extent is generative AI currently being used at your bank? Can you provide specific examples or use cases?
3. What do you believe are the main advantages and disadvantages of using generative AI in banking operations?

AI and relationship management in bank lending

1. What do you see as the key drivers for implementing generative AI in the bank lending process?
2. In what specific ways do you think generative AI can improve operational efficiency for relationship managers in bank lending?
3. How do you anticipate relationship managers will adapt to the integration of generative AI into their roles? What kind of training or support might they need?
4. In your opinion, what are the primary opportunities and challenges of integrating generative AI into relationship management within bank lending services?

AI and customer experience

1. How do you think integrating generative AI into relationship management practices will impact the customer experience in bank lending? Can you provide potential positive and negative outcomes?

Further insights

1. What specific training or support do you think relationship managers need to effectively integrate generative AI into their roles?
2. How do you think the use of generative AI in relationship management will impact customer trust and loyalty?
3. What strategies do you think are necessary to overcome the challenges associated with integrating generative AI into relationship management in bank lending?
4. Are there any additional insights or recommendations you would like to share regarding the use of generative AI in bank lending services?