Gordon Institute of Business Science
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The Influence of AI-Enabled Tool Adoption, Digital Footprints, and SME Credibility on Loan Approvals: A Quantitative Study of South African SMEs

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Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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Abstract

Information asymmetry remains a critical barrier to Small and Medium Enterprises (SMEs) financing in South Africa, with traditional credit assessment mechanisms failing to recognise the creditworthiness of viable enterprises. Digital transformation and AI-enabled technologies present potential new signalling mechanisms that could bridge this gap. This quantitative study examined whether AI-enabled tool adoption, digital footprints, and SME credibility influence loan approval outcomes for South African SMEs that applied for loans within a 12-month period. Data were collected through structured surveys and analysed using Bayesian logistic regression to test four hypotheses grounded in signalling theory and information asymmetry theory.

Results revealed that AI adoption demonstrated strong model-level evidence and moderate interaction effects with credibility, both receiving partial support/association. However, digital footprints and credibility independently showed insufficient evidence to reliably predict loan approval. Credibility functions as a complementary signal that gains relevance when combined with AI adoption or hard financial metrics.

Traditional financial indicators such as firm size, operational maturity, and cash flow capacity remain primarily associated with lending decisions. The study concludes that while digital signals are acknowledged by lenders, they function as transitional indicators requiring institutional maturation before becoming decisive factors in South Africa's conservative banking environment.

Keywords: information asymmetry, AI-enabled tools, digital footprints, SME financing, signalling theory

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List of Acronyms

4IR	Fourth Industrial Revolution
AI	artificial intelligence
AIA	AI-enabled tool adoption
AVE	average variance extracted
B2B	business-to-business
BF	Bayes factors
BF_{10}	A Bayes factor that compares a specific model to the null model
CFA	confirmatory factor analysis
CFI	Comparative Fit Index
CR	composite reliability
CRE	SME credibility
CrI	credible intervals
CSI/ESD	Corporate Social Investment / Enterprise and Supplier Development
DFI	development finance institutions
DFP	digital footprints
DSBD	Department of Small Business Development
DT	digital transformation
dtic	The Department of Trade, Industry and Competition
DV	dependent variable
EFA	Exploratory Factor Analysis

FinTech	financial technology
FSPs	financial service providers
HTMT	heterotrait-monotrait ratio of correlations
ICT	Information and Communication Technology
IVs	independent variables
KMO	Kaiser-Meyer-Olkin
MCMC	Markov Chain Monte Carlo
ML	Machine Learning
MLR	robust maximum likelihood estimation
OR	Odds ratios
PE	private equity
RMSEA	Root Mean Square Error of Approximation
SA	South Africa
SCF	supply chain finance
SDGs	United Nations Sustainable Development Goals
SEDA	Small Enterprise Development Agency
SMEs	Small (and) Medium Enterprises
SMMEs	small, micro and medium enterprises
SPSS	Statistical Package for Social Sciences
SRMR	Standardised Root Mean Square Residual
TLI	Tucker-Lewis Index
VC	venture capital

Chapter 1: **Introduction to Research Problem**

1.1 Introduction

Small and Medium Enterprises (SMEs) are widely recognised as cornerstones of global economic prosperity, serving as a significant source of employment across both developing and developed economies (Rao et al., 2023). Their success and sustainable growth are important for global economic development as they contribute towards job creation, promote innovation, and aid in narrowing the income gap, all of which are aligned with the United Nations Sustainable Development Goals (SDGs) (Fazal et al., 2025; Rao et al., 2023).

In South Africa, SMEs are particularly crucial, as they are considered to be the main source of employment creation (Baloyi & Khanyile, 2022) and are central to the government's ambitious target of creating 11 million jobs by 2030, with SMEs generating 90% of these jobs (Baloyi & Khanyile, 2022). Therefore, the success of the SME sector is not merely about economic goals, but a shared goal for the entire society, closely linked with the well-being and prosperity of millions.

The constraint is a major barrier to SMEs when it comes to accessing finance, particularly in the form of credit, required to expand business operations and drive South Africa's economic recovery (Rao et al., 2023; Zheng et al., 2025). This constraint is a major barrier to the growth of SMEs and an important factor holding back the development of SMEs (Guo et al., 2023). This problem is especially true in the case of Africa and remains persistent, translating into a high SME failure rate, exemplified by the worrying 70% business failure rate within the first five years in South Africa (Okoye et al., 2024). This limitation of SMEs to access the funding that they require means the aspirations of countless entrepreneurs are curtailed, business growth is constrained, slowing down innovation and economic transformation (Baloyi et al., 2022). Understanding and addressing these financing challenges is thus not just an academic exercise but a moral imperative, calling governments and financial institutions to action to better promote financial access for SMEs (Rao et al., 2023).

Taking a closer look at the barriers to SME financing, it is evident that SMEs are often unable to secure formal loans due to incomplete, unaudited or informal financial records; their inability to provide sufficient collateral or strong credit history is another challenge (Vaghera & Mashekwa, 2025). These factors are often viewed as non-negotiable requirements for formal loans by banks and other FIs (Quartey et al., 2017). As a result, SMEs are forced to turn to more expensive forms of debt financing, which traps them in a cycle of constrained growth and limited scalability (Rao et al., 2023).

The widespread SME financial exclusion is caused by deep-rooted problems that make it difficult for them to secure credit (Vaghera & Mashekwa, 2025). Scholars, Asongu and Le Roux (2017) and Li et al. (2024) posit that the major systematic barrier to SME financing is information asymmetry, which is an imbalance of information between lenders and borrowers. This is a situation whereby one party (financial institutions) lack sufficient insight into another party's (SMEs) operations, financial health, or credibility, often due to informal or incomplete records, leading to unequal decision-making power (Calabrese et al., 2021). As a result, banks and other traditional lenders perceive SMEs as high-risk borrowers (Vaghera & Mashekwa, 2025).

Interestingly, some SMEs adopt the "zero-leverage" phenomenon, in which they choose not to take on debt, driven by a preference for financial flexibility. However, this counterintuitive behaviour does not necessarily signify a reduction in information asymmetry. Instead, it may suggest that SMEs are deliberately avoiding a financial system that fails to recognise their legitimacy (Gama et al., 2024). This high prevalence of information asymmetry-related problems in SMEs exacerbates the situation (Baloyi & Khanyile, 2022).

Signalling theory is an important theoretical lens for understanding this issue of how organisations communicate in the face of information asymmetry (Colombo, 2021; Le et al., 2024; Mushtaq et al., 2022; Rao et al., 2023; Spence, 2002). Drawing on the signalling theory (Rao et al., 2023) in the domain of entrepreneurial finance, he posits that firms can purpose-fully allow the ability to signal a venture's qualities by employing various observable actions and features, because it is important as it reduces uncertainty and enhances credibility, earning authority and resources from potential investors (Colombo, 2021; Le et al., 2024).

It explains how one party (the signaller) conveys information to another party (the receiver) to reduce information asymmetry (Rao et al., 2023).

In recent years, the Fourth Industrial Revolution (4IR) came with a wave of emerging disruptive digital technologies across industries, with artificial intelligence (AI) expected to radically transform business operations, particularly in the financial industry (Mhlanga, 2020; Oldemeyer et al., 2025). Presently, financial technology (FinTech) companies use AI to offer loans to low-income workers and SMEs (Mhlanga, 2021), demonstrating that this technological revolution offers a beacon of hope for overcoming long-standing financial barriers.

Given its mature financial sector and growing digitisation trends, South Africa is an exciting place to study these changes, having witnessed the rise of AI-powered FinTech innovations (Hassan, 2024). Therefore, it is clear that AI is essential for achieving financial inclusion because it promises to enhance access to credit facilities through risk assessment, scam detection, and personalised financial services that are powered by AI (Fazal et al., 2025).

From this perspective, no longer is the question whether or not technology will change how SMEs access finance, but how deeply and effectively it can shed light on the financial world for people who have previously been financially excluded (Hassan, 2024; Mhlanga, 2020).

In the context of this study, the adoption of AI-enabled tools and the creation of robust digital footprints function as powerful, credible signals (Guo et al., 2023; Huang et al., 2025; Mushtaq et al., 2022). For instance, a firm's engagement in digital transformation "improves the quality of external information disclosure", which in turn releases a signal to attract investors by enhancing transparency (Guo et al., 2023, p. 968; Mushtaq et al., 2022). This process helps alleviate financing constraints for Small and Medium-sized Enterprises (SMEs) by elevating their information transparency and reducing information asymmetry with fund providers, thereby boosting the confidence of external stakeholders (Guo et al., 2023; Mushtaq et al., 2022; Quartey et al., 2017).

In the context of SMEs applying for loans, the SMEs are the signalers and the financial institutions are the receivers. This may result in SMEs conveying their inherent qualities and legitimacy to prospective investors/lenders/financiers by displaying certain attributes or actions (Colombo, 2021).

1.2 Research Problem

The problem with South Africa's SME sector is not a scarcity of capital but rather a persistent lack of access to it (Baloyi et al., 2022). While commercial banks and development finance organisations hold billions of dollars targeted to support SMEs, the estimated funding shortfall is between ZAR86 billion and ZAR346 billion (Baloyi et al., 2022).

The paradox is that while funds exist, they remain underutilised because many SMEs fail to qualify under conventional lending criteria. This suggests that South Africa has no shortage of financial instruments, but a shortage of innovation that supports the development of lending instruments (Baloyi & Khanyile, 2022). Baloyi & Khayile (2022), claim that the lack of financial innovation is the most significant driver of the country being stuck with the recurring funding gap. Traditional risk evaluations that strongly rely on collateral, official financial records, and formalised contexts exclude most of the SMEs operating in dynamic but mostly informal situations (Rao et al., 2023). Consequently, high-potential entrepreneurs are denied access to funding sources, deepening the funding gap. Addressing this gap calls for re-evaluating assessment methods and using new technologies, including artificial intelligence, to provide more inclusive, adaptable, and precise means of assessing the creditworthiness of SMEs (Sharma & Sharma, 2024).

This tension between available funds and inaccessible financing can be further understood through the lens of signalling theory, which sheds light on the communication gap between entrepreneurs and financiers. In this complex dance, SMEs take on the role of signalers, and financial institutions become receivers (Colombo, 2021). To access needed finance, entrepreneurs must constantly find ways to signal legitimacy, credibility, and potential, often in contexts where the usual sources of evidence, such as collateral and audited accounts, do not exist or are insufficient (Colombo, 2021).

Despite the importance of the signalling theory in explaining how SMEs signal trustworthiness, the literature remains disjointed and lacks a coherent model for leveraging everyday digital tools and data as effective quality signals (Guo et al., 2023). This disconnect is particularly acute in emerging economies like South Africa, where many SMEs struggle with low digital maturity, leaving them poorly equipped to communicate their true potential in ways that will resonate with financiers.

Emerging research suggests that digital footprints and AI-generated indicators could bridge this divide, serving as credible proxies for business quality when conventional documentation falls short (Le et al., 2024). However, as Colombo (2021) argues, the lack of an integrative understanding of what and how SMEs should signal leaves both entrepreneurs and lenders navigating in the dark, entrepreneurs unable to access capital despite their viability, and financiers unable to unlock the billion in funds they hold (Baloyi & Khanyile, 2022).

Against this backdrop, the researcher seeks to examine whether AI-enabled digital tools adoption, SME credibility and digital footprints can serve as effective signals, critical in reducing the perceived SME lending risk by banks and other financial institutions, thus improving loan approval outcomes (Guo et al., 2023; Li et al., 2024; Mhlanga, 2021). Examining these modern signals through a quantitative lens contributes to a deeper understanding of digital transformation as a lever for financial inclusion in South Africa's SME sector (Schwaeke et al., 2025).

Furthermore, Colombo (2021) emphasises the lack of comprehensive guidance for entrepreneurs on how to effectively use signals in their communications with prospective financiers, given the evolving landscape of entrepreneurial finance and the emergence of new communication channels. Forming the basis for the claim that AI has the power to potentially enhance signals from entrepreneurs (Okoye et al., 2024). This study uses a quantitative approach to explore how the adoption of AI tools, SME credibility, and digital footprints influence loan approval decisions.

1.3 Purpose Statement

This gap is especially evident in emerging economies like South Africa, where SMEs operate with limited digital maturity (Ayinaddis, 2025; Oldemeyer et al., 2025). Furthermore, AI's potential to transform SME lending is promising, yet few studies have examined how everyday AI enabled tools, such as WhatsApp Business, digital payment systems, and social media visibility, interact with perceived credibility and online presence to influence loan approval outcomes in the South African context (Hassan, 2024; Kshetri, 2021; Li et al., 2024).

1.3.1 Purpose of the Study

The study aims to investigate how certain signalling mechanisms used by South African SMEs affect loan approval outcomes. This was achieved by examining three key constructs: (1) SME credibility, (2) digital footprint strength, and (3) AI adoption as strategic signals utilised to help mitigate information asymmetry between loan applicants and financiers.

By analysing the relationship between these constructs and loan approval outcomes, the study aims to provide empirical evidence on whether these non-traditional signals are associated with improved access to finance among South African SMEs. This will contribute to signalling theory by testing whether technology-enabled signals reduce information asymmetry in lending decisions, with potential implications for both SME digital strategies and lender assessment frameworks. The next section outlines the specific research objectives of this theoretical foundation.

1.3.2 Research Objectives

1. To examine the relationship between non-financial signals (i.e., digital footprints, AI adoption, credibility) and their ability to secure financing.

2. To identify which signals presented by SMEs are most strongly associated with positive financing outcomes.

3. To apply signalling theory by testing the role of non-financial, technology-enabled signals as credible indicators of SME creditworthiness in an emerging market context.

Chapter 2: Literature Review

2.1 Introduction

This section presents relevant theories concerning the research objectives and critically reviews the literature to highlight gaps. The chapter commences with Section 2.2, which provides the definitions of SMEs, and Section 2.3 presents the South African funding landscape. Section 2.4 presents the theoretical foundation covering information asymmetry and signalling theory. Empirical research findings are presented in Section 2.5. The reinforcement of the theory and the constructs is presented in Section 2.6. The key research gaps are presented in Section 2.7, followed by the conceptual framework in Section 2.8. The review concludes with Section 2.9 summarising insights and linking them to the research objectives.

2.2 Definitions of SMEs

The definitions of SMMEs differ significantly from one country to another, and in some cases, they also change across national borders.

In South Africa, the National Small Business Act of 1996 formally classified SMMEs as micro, small or medium enterprises based on a prescribed criterion as illustrated in Appendix D, categorising entities according to number of employees, level of turnover and profitability, sector and aggregated value of assets of an enterprise (National Small Enterprise Act, 1996). However, in the recent amendment to the Act (National Small Enterprise Amendment Act, 2024), the definition has been narrowed to "small enterprise", a separate and distinct business entity, which includes its branches and subsidiaries, if any. These entities are identified as operating in any sector or sub-sector of the economy. What is worth noting is that the main amendment to the act is that the power to determine these "prescribed criteria" now rests with the Minister, giving them the power to make regulations, setting the criteria for the classification of micro, small, and medium enterprises, taking into account factors such as inflation and macroeconomic shifts in the economy. With that said, for the purpose of this study, the research adopts the definition of SMMEs as classified by the original Act of 1996.

2.3 South African Funding Landscape

The South African small business finance environment is characterised by a plethora of funders and financial products, yet it has been facing serious issues regarding access to and suitability of financing for SMMEs (Finfind, 2025). A persistent funding shortage and disparity between funding requirements and availability continue to hinder SMMEs growth and sustainability (Finfind, 2025). The landscape consists of traditional financial institutions as well as more and more alternative lenders, each having disparate products and availability for other MSME segments.

Table 2.1 provides an overview of the environment of small business financing in South Africa, ranging from debt financing to grant funding.

Table 2.1: The South African Funding Landscape Overview

Financial instrument	Description	Main providers in SA	Finfind product count/share
Debt (bank loans, term loans, overdrafts, working capital)	Repayable loans (secured/unsecured) for working capital, capex, and expansion	Commercial banks, non-bank lenders, DFIs (IDC, SEFA), FinTech lenders, merchant cash-advance providers	394 products (≈58.7%). (Menzies et al., 2025)
Equity (venture capital, private equity, angel investment)	Ownership stakes in exchange for capital	VC firms, angel networks, PE, DFIs (IDC equity deals), corporate funds	181 products (≈26.9%). (Menzies et al., 2025)
Grants (non-repayable)	Subsidy/conditional funding for training, capex, export, R&D	DSBD, dtic, SEDA, foundations, corporate CSI/ESD programmes	40 products (≈5.9%). (Menzies et al., 2025)

Source: (Menzies et al., 2025).

2.4 Theoretical Foundation

2.4.1 Information Asymmetry

Small and medium-sized enterprises (SMEs) both globally and, particularly, in developing economies, such as South Africa, experience substantial constraints regarding accessing finance, largely as a result of asymmetric information between them and the financial intermediaries (Guo et al., 2023; Rao et al., 2023). This problem is a known severe obstacle that hampers the growth and development of SMEs in general and the economy as a whole (Guo et al., 2023).

Information asymmetry is an underlying situation in which one party in a transaction has more or better information than the other, whose actions or decisions are affected by the information gap in ways potentially detrimental to them (Mhlanga, 2021; Mushtaq et al., 2022). In terms of SME financing, the lenders generally cannot obtain all the project risk factors, the true health condition of an SME, or accurate SME creditworthiness (Ma et al., 2019; Mhlanga, 2021).

The situation becomes worse because SMEs usually lack knowledge about proper information disclosure methods and maintain less complex financial systems than larger businesses. SMEs face difficulties in presenting essential financial and nonfinancial information to potential lenders and credit rating agencies because they lack accurate methods to report intangible assets, internal governance quality and social responsibility fulfilment (Guo et al., 2023; Ryan et al., 2014, cited in Guo et al., 2023).

This fundamental information imbalance directly increases the cost of debt financing for SMEs (Claus, 2011, cited in Mushtaq et al., 2022) and can lead to inefficient allocation of capital across the economy (Li et al., 2023).

2.4.1.1 Core Problems Arising from Information Asymmetry

The three pivotal problems resulting from information asymmetry; Credit rationing, adverse selection, and moral hazard, are discussed below.

Firstly, information asymmetry is one of the main reasons for credit rationing, the condition in which banks are obliged to decline term loan applications or grant only a part of the amount requested by applicants even when they are objectively financially viable with profitable projects (Ma et al., 2019; Anastasiou et al., 2025).

This is especially the case in less mature and flawed credit markets, which are common in underdeveloped economies, where bank loan approvals increasingly rely on a firm's size rather than on quality (Ma et al., 2019).

Secondly, information asymmetry often leads to adverse selection (ex-ante), which refers to the risk or problem that arises before a transaction takes place. In this instance, before loan agreements are completed, lenders face difficulties in correctly distinguishing between risky and safe borrowers (Mhlanga, 2021; Motta & Sharma, 2020). The less creditworthy firms try to hide their actual risk level when seeking loans. The inability to identify risk levels prevents lenders from creating suitable interest rates and terms, which might cause all SMEs to receive unaffordable interest rates that block access to loans (Mhlanga, 2021; Motta & Sharma, 2020). The unobservable risk factors that exist before loan approval restrict SMEs from obtaining necessary funding because lenders cannot assess their true risk profile (Anastasiou et al., 2025).

Lastly, the moral hazard (ex-post) occurs after loan approval because the lender cannot observe borrower actions or efforts. This condition may lead to borrowers selecting risky projects that have a higher chance of failure or acting opportunistically in ways that only benefit them and, as such, increase the risk for the lender (e.g., misusing funds or not putting in enough effort), resulting in high chances of loan default and threatening project success (Mhlanga, 2021).

2.4.1.2 Traditional Information Asymmetry Mitigation Strategies and Their Shortcomings for SMEs

Historically, banks heavily relied on collateral as a primary instrument to mitigate default risk, especially when lending to informationally opaque SMEs (Motta & Sharma, 2020; Yang et al., 2025). The majority of SMEs operating in emerging markets face restricted access to formal financing because they do not possess enough fixed assets or conventional collateral (Ma et al., 2019; Motta & Sharma, 2020; Yang et al., 2025). The use of self-financing as a "credible factor" to demonstrate project quality remains insufficient for banks to approve loans to small businesses because they prefer larger enterprises with more visible assets (Ma et al., 2019).

Furthermore, when SMEs present financial statements that have undergone external audits, it displays transparency, signalling higher business quality and reducing information asymmetry (Motta & Sharma, 2020). However, research findings about how external audits affect SMEs' ability to secure funding have not produced definitive results (Governments and SMEs Financing, 2025). Government procurement auditing provides a more detailed assessment of business systems and compliance through its extensive review process compared to traditional financial audits (Governments and SMEs Financing, 2025).

While external audits and government procurement assessments serve as formal mechanisms to signal transparency and compliance, SMEs can also create strategic signals to demonstrate their quality and legitimacy when approaching potential investors (Colombo, 2021; Rao et al., 2023). For example, a company that demonstrates its commitment to Information and Communication Technology (ICT) through substantial investment and extensive usage will likely receive better credit terms from banks because it signals its innovative nature and creditworthiness (Mushtaq et al., 2022).

2.4.2 Signalling Theory

These strategic actions by SMEs, such as investing in ICT to signal innovation and creditworthiness, reflect the core principles of signalling theory, which explains how firms convey their underlying quality to external stakeholders through observable cues (Mushtaq et al., 2022). It is a theory that explains how organisations can deliberately send out reliable information to lower their risk and strengthen their position in front of external stakeholders, such as financiers (Colombo, 2021).

2.4.2.1 The Foundational Role of Signalling in Mitigating Information Asymmetry

Signalling theory is a valuable framework for the explanation of firms' and especially SMEs' capacity to overcome information asymmetry in credit markets by conveying quality and legitimacy to prospective financiers (Colombo, 2021; Wang et al., 2025).

Additionally, credible signals are essential to differentiate high-quality firms from low-quality ones, thereby reducing lenders' perceived risks and potentially lowering financing costs (Wang et al., 2025).

2.4.2.2 Traditional Signals of SME Credibility

Traditionally, factors such as collateral requirements and audited financial statements have been valuable indicators to lenders. Collateral, particularly fixed assets, has been found to connote higher project quality and lower risk profiles, therefore encouraging SMEs to deliver and repay loans according to contractual standards (Motta & Sharma, 2020). Furthermore, when enterprises self-finance for a project, it acts as a "credible factor" to lenders in that it discloses the risk-bearing ability of the firm and therefore signals project quality (Ma et al., 2019).

It is also worth noting that other scholars agree that networks and social capital, as well as membership in local business associations, are another kind of signal that facilitates decisions through the intermediation of risk and the creation of trust (Forstner et al., 2025; Nguyen & Canh, 2021; Zhang et al., 2025)

2.4.2.3 Digital Transformation and AI-enabled tools as New Signalling Mechanisms

The advent of digital finance technology and digital innovation has introduced new and highly efficient ways for SMEs to communicate their credibility (Guo et al., 2024; Li et al., 2023; Yang et al., 2025).

Digital transformation significantly reduces financing barriers by enabling SMEs to improve the quality of external information disclosure, thus lowering information asymmetry between firms and financial institutions (Guo et al., 2024). This enables a more impartial enterprise image with actual repayment willingness and ability (Guo et al., 2024).

Machine learning algorithms and AI-enabled applications are transforming credit risk analysis by employing various data sources other than financial records (Andronie et al., 2023; Mhlanga, 2021). The applications can differentiate high- and low-quality SMEs to improve the accuracy of credit risk forecasting (Belhadi et al., 2025).

ICT and AI tools enable overcoming information asymmetry by accessing various online platforms and social networks, generating a great deal of information about individuals and companies (Mhlanga, 2020). Therefore, online information can potentially serve as new "signals" of creditworthiness (Mushtaq et al., 2022).

2.4.2.4 Digital Footprints and SME Credibility for Loan Approvals

Digital footprints, such as data from online shopping sites, social media, mobile data (text messages, call records, and GPS), and company registers, are increasing in significance for SME credibility assessment (Li et al., 2023; Mhlanga, 2021; Yang et al., 2023). AI-powered mobile lending applications, like the "Branch" application that operates in several emerging markets, like South Africa, utilise machine learning to analyse thousands of data points from mobile phone data to determine creditworthiness and provide collateral-free loans to individuals and small businesses (Mhlanga, 2021). This is direct evidence of AI-enabled tools and digital footprints generating signals for loan approval in the South African context.

Financial service providers and banks are progressively adopting unique digital footprints to mitigate information asymmetry and alleviate financing constraints, particularly for light-asset companies (Yang et al., 2025). This systematic evaluation of non-traditional data enables a multi-dimensional credit evaluation system that increases information transparency and reduces adverse selection costs for capital suppliers (Li et al., 2023).

SMEs with high ICT usage are less likely to experience financing constraints, as banks consider their ICT adoption strategy a positive signal of willingness to innovate and a dynamic mirror of their business operations, which enhances their loan repayment capacity (Mushtaq et al., 2022).

2.4.2.5 Impact on Loan Approvals and Financial Inclusion

The deployment of machine learning algorithms in FinTech lending allows for more accurate creditworthiness estimates, facilitating credit services and promoting financial inclusion (Andronie et al., 2023). From the demand side, by effectively transmitting good information with the help of AI-based tools and electronic footprints, SMEs can reduce information asymmetry, build lender trust and have greater credit amounts on more favourable terms (Mushtaq et al., 2022).

2.5 Empirical Research Findings

2.5.1 Information Asymmetry in SME Financing: Global and African Context

Empirical data reveal that information asymmetry continues to be a significant constraint to the global growth of SMEs (Rao et al., 2023). It is typically more pronounced in developing nations (Nguyen & Canh, 2021). For example, research has indicated that banks tend to prefer big businesses because of their perceived asset size and proven track record, even as small firms provide adequate collateral (Ma et al., 2019).

Banks also think about how much funds an enterprise holds in hand as a "credible factor" that reflects the quality of a project rather than the collateral size it has (Ma et al., 2019).

External audit certification is thought to make SME financial statements more trustworthy and make it easier for SMEs to get loans, but the proof isn't always clear, and many SMEs don't do it because of the costs (Kinyua et al., 2025).

2.5.2 Technology Adoption and Digital Financial Inclusion in Africa

In the South African and general African scenario, literature indicates that the pivotal role of technology adoption and digital financial inclusion (DFI) comes into play in addressing these longstanding finance exclusion issues. David Mhlanga's research shows how AI and Machine Learning (ML) are being used to overcome information asymmetry, adverse selection, and moral hazard, particularly for vulnerable groups like small and medium enterprises and low-income groups who lack traditional collateral or credit history (Mhlanga, 2021; Mhlanga, 2020).

AI-based applications can mine alternative data sources like public data, satellite pictures, company registers, social media data (SMS, Messenger apps, call logs, contacts, and GPS), and even online retail behaviour for crafting detailed credit histories (Mhlanga, 2021). This practice facilitates non-collateral lending and instant credit scoring, as shown by unsecured lending apps like Branch (available in countries such as Kenya, Nigeria, India, and Mexico) and analytical firms like FarmDrive (Mhlanga, 2021).

Even in South Africa, MyBucks has successfully used AI technology to scrape data from potential borrowers' phones to generate lending profiles, significantly reducing loan default rates (Mhlanga, 2021).

2.5.3 Digital Transformation Challenges for South African SMEs

The adoption of digital transformation (DT) and new technologies by South African SMEs has challenges attached. South African SMEs are referred to as "non-subsidised firms" (Jeza & Lekhanya, 2022), which means greater reliance on self-capital or market financing. Despite the strengths of DT in increased exposure in the market and sales, South African SMEs have challenges such as the high initial establishment costs, high constant digital upkeep costs, and the rapid pace of technological change (Jeza & Lekhanya, 2022). This can lead to incomplete or ineffective adoption of digital technologies, thereby potentially weakening their ability to employ the use of these technologies in effective signalling and increased credibility in the financial market (Jeza & Lekhanya, 2022). The scarcity of literature on SME finance in the Middle East, Asia-Pacific, and Africa underscores the need for further research to understand these facts of emerging markets (Rao et al., 2023).

2.5.4 Trends and Drivers of AI-Enabled Tool Adoption in SMEs

One of the primary reasons to adopt AI and Machine Learning (ML) in finance is that they can reduce information asymmetry, adverse selection, and moral hazard, hence historically hindering access to finance by SMEs (Mhlanga, 2021; Mhlanga, 2020; Yang et al., 2024).

Furthermore, FinTech firms and financial service providers (FSPs) are increasingly utilising AI for important operations, including risk detection, measurement, management, fraud identification, credit scoring, and customer service (Belhadi et al., 2025; Mhlanga, 2020; Mhlanga, 2021; Paul, 2019). Scholars (Belhadi et al., 2025) posit that AI and ML models give more accurate predictions of credit risk, especially when traditional data is limited.

When looking at Digital transformation (DT), often with AI support, it has been considered a prerequisite for SME sustainable survival and organisational resilience development, particularly against economic crises and volatile market volatility (Guo et al., 2023; Jeza & Lekhanya, 2022; Klein & Todesco, 2021).

It is worth noting that Digital financial inclusion (DFI) is increasingly being encouraged by governments globally and financial institutions to boost the financial access of excluded groups, including SMEs. Digital financial services powered by AI, including data-driven microlending and digital wallets, facilitate easier money management and business growth for entrepreneurs (Li et al., 2023; Wei et al., 2025; Yang et al., 2024).

Additionally, AI may enhance operational efficiency, financial performance, business model innovation, and customer satisfaction for firms (Guo et al., 2023).

2.5.5 Digital Footprints and SME Credibility

2.5.5.1 Utilising Alternative Data

AI and ML use "digital footprints" – non-traditional sources of information to establish SME creditworthiness. These include mobile data (call logs, text messages, contacts, GPS), online retailers, social network activity, public information, satellite photography, and company registries (Mhlanga, 2021). This is capable of overcoming the lack of traditional credit history and collateral, which is normally prejudicial to SMEs (Mhlanga, 2021).

2.5.5.2 Increased Information Transparency

Digitalisation allows SMEs to accurately document and disclose a wide range of information, such as tangible assets, intangible assets, marketing information, accounting records, taxation, and social security. AI can derive important information from massive amounts of unstructured transactional data and yield a more objective and multi-dimensional enterprise profile for risk assessment (Guo et al., 2023; Li et al., 2023).

2.5.5.3 Signalling Quality

SMEs who use and effectively utilise ICT and AI-enabled tools can convey positive signals to lenders, indicating their innovation intent, operating dynamism, and better capacity to repay loans (Mushtaq et al., 2022). This builds confidence and can lead to improved credit terms. Some financial indicators are also responsible for enhancing the creditworthiness of an SME. For example, maintaining a current ratio of 2.0 to 3.8, financial leverage management (below 0.18 in the case of agricultural

SMEs), widening profit margins on sales, and growth on the strength of internal capital (in contrast to excessive long-term debt for asset acceleration) are all factors in creditworthiness (Belhadi et al., 2025).

In addition, relationship-based lending, whereby long-term, favourable relationships with meritorious top-level businesses (LEs) in its value chain are established, can further advance the credit terms of an SME, particularly those of supply chain finance (SCF) (Belhadi et al., 2025; Rao et al., 2023).

2.5.6 Barriers and Enablers of AI Adoption for South African SMEs

2.5.6.1 Barriers to AI Adoption

Scholars such as Jeza and Lekhanya (2022) argue that, in general, the perceived high upfront cost and ongoing, costly maintenance due to ever-changing digital technology are significant barriers for SMEs, particularly in South Africa, where the majority of SMEs have not fully adopted digital transformation and need intensive upgrading in the digitalisation of their operations to properly leverage emerging technologies (Jeza & Lekhanya, 2022).

Additional barriers to AI adoption for SMEs are the data scarcity, because while AI is data-fed, it can sometimes be hard to obtain complete, context-specific datasets (Belhadi et al., 2025)

Furthermore, the lack of awareness and trust results in a "knowledge gap" among SME owners, regarding available financial resources, as well as the "benevolence gap", reflecting lenders' reluctance to engage with SMEs (Kumar & Rao, 2015). Lastly, the resource-constrained nature of SMEs, coupled with their limited strategic options, renders them particularly vulnerable during periods of crisis and may hinder the successful implementation of digital strategies (Forstner et al., 2025).

2.5.6.2 Enablers of AI Adoption

There are significant enablers that SMEs can leverage when adopting AI, as demonstrated by other scholars. Firstly, a mature regional digital financial environment is conducive to the efficacy of digital transformation in mitigating SME finance barriers (Guo et al., 2023; Li et al., 2023). Secondly, the leadership and expertise of the SME matters; whereby the attitude, traits and purpose for growth or risk, or IT expertise of the owner/manager are important to stimulate ICT and AI use in South African SMEs (Arendt, 2008; Gono et al., 2016).

Thirdly, the appropriate policies are essential in helping SMEs leverage their networks to drive innovation. These can be in the form of tax incentives, improved access to credit, and partnerships with financial institutions (Guo et al., 2023; Zhang et al., 2025).

Lastly, Rao et al. (2023) posit that AI has brought open banking protocols that allow clients to share financial information with third-party service providers to make more-informed lending decisions.

2.6 Reinforcement of theory and constructs

In South Africa, several research gaps emerge that deepen the argument for the proposed study. The direct relationships outlined in the study, specifically the combined influence of AI-enabled tool adoption, digital footprints, and SME Credibility on loan approvals for South African SMEs, have not been investigated in a single, integrated study. However, Literature provides substantial support for the individual components/constructs of the research objectives and hypotheses, confirming the relevance and timeliness of the research. These are discussed below.

2.6.1 SME Financial and Nonfinancial Signals and Securing Finance

The literature strongly supports the idea that SMEs use various signals to mitigate information asymmetry and secure financing (Connelly et al., 2011; Spence, 2002). Lenders face challenges in assessing the creditworthiness of SMEs due to informational opacity and a lack of traditional financial records (Guo et al., 2024; Kinyua et al., 2025; Sharma & Sharma, 2024). Consequently, SMEs must actively signal their quality and financial attractiveness to receive credit (Aktekin et al., 2018; Ma et al., 2019).

The signalling theory provides a robust framework for understanding how SMEs can convey their quality and credibility to potential lenders (Spence, 2002). Traditional signals include tangible assets for collateral, audited financial statements, and established credit histories (Motta & Sharma, 2020; Watson & Wilson, 2002). However, many SMEs, especially in the South African context, lack these conventional signals (Baloyi & Khanyile, 2022). This creates a critical research gap concerning the efficacy of non-traditional, digitally-derived signals in mitigating information asymmetry for SMEs in emerging markets.

2.6.2 Digital Transformation and Contemporary Signalling

The rapid digital transformation of the global economy presents both challenges and opportunities for SME financing (Guo et al., 2024; Jeza & Lekhanya, 2022). The rise of Financial Technology (FinTech) and AI is reshaping financial services, offering innovative ways to assess credit risk and promote financial inclusion (Kshetri, 2021; Mhlanga, 2021). AI-enabled credit scoring models, which can process vast amounts of alternative data, have shown the potential to evaluate applicants who lack traditional credit histories, a characteristic common among underserved populations and SMEs (Li et al., 2024). These models leverage "weak signals" or "digital footprints", data not conventionally used to evaluate creditworthiness, create a more accurate and individualised risk profile, thereby reducing reliance on group characteristics that lead to statistical discrimination (Li et al., 2024).

Despite these technological advancements, several gaps persist in the literature, particularly within the South African context. First, while global studies highlight the potential of AI and digital data in finance (Jagtiani & Lemieux, 2019; Li et al., 2024), there is a scarcity of research focused specifically on the adoption and impact of these technologies among South African SMEs. Rao et al. (2023) explicitly identified SME financing in Africa as an under-researched region, calling for more scholarly attention. The unique socio-economic landscape of South Africa, characterised by high inequality and a significant informal sector, necessitates context-specific research that cannot be directly extrapolated from studies in developed or other emerging economies (Baloyi & Khanyile, 2022).

Second, much of the literature on digital finance focuses on the supply side; on how FinTech firms and banks are changing their lending practices (Calabrese et al., 2021; Wei et al., 2025). There is a corresponding lack of research from the demand side, exploring how SMEs themselves adopt and leverage AI-enabled tools to enhance their credibility and generate positive signals for lenders (Guo et al., 2024). The proposed study directly addresses this by positioning AI-enabled tool adoption as a deliberate strategic action by SMEs to improve their financing prospects.

Third, the concept of a digital footprint as a comprehensive signal of SME credibility is still nascent. While studies have examined specific digital data points like social network activity or mobile phone usage (Li et al., 2024; Mushtaq et al., 2022), a holistic understanding of how the aggregation of an SME's online presence and digital transactions and its digital footprint functions as a credible signal to lenders is underdeveloped. This study aims to conceptualise and empirically test the influence of this multifaceted digital signal on loan approvals.

Finally, the interplay between these new digital signals (AI tool adoption, digital footprints) and traditional indicators of SME credibility (e.g., managerial experience, trustworthiness) has not been thoroughly investigated. It is unclear whether these digital signals complement, substitute, or interact with traditional credibility markers in the eyes of lenders. For example, does a strong digital footprint compensate for a lack of tangible collateral? Does the use of sophisticated AI-enabled financial management tools by an SME signal a higher level of managerial competence, thereby increasing its perceived credibility (Bryan et al., 2024)? Answering these questions is crucial for developing a contemporary model of SME financing in the digital age.

2.7 Research Gaps

2.7.1 Geographical and Contextual Gap in SME Financing Research

There is a significant scarcity of research on SME financing within the African context, particularly in South Africa (Rao et al., 2023). Most existing studies are concentrated in Europe and America, and their findings may not be generalisable to the unique economic and institutional environments of emerging African markets.

The South African SME sector faces specific challenges, such as a high discontinuity rate, unsupportive regulatory frameworks, and the legacy of economic inequality, which are not fully captured by international studies (Baloyi & Khanyile, 2022).

2.7.2 Demand-Side Perspective on Digital Transformation and AI Adoption

The literature on digital finance predominantly focuses on the supply side (i.e., lenders' use of technology) (Guo et al., 2024). There is a lack of research examining how SMEs, from the demand side, proactively adopt AI-enabled tools as a strategic signal to enhance their creditworthiness and alleviate financing constraints. While studies acknowledge that SMEs are adopting digital technologies, the specific influence of this adoption on their ability to secure formal loans remains an under-researched area, especially in South Africa (Jeza & Lekhanya, 2022).

2.7.3 The Role of Digital Footprints as a Holistic Signal

Although the use of alternative data or "weak signals" in credit scoring is gaining attention (Jagtiani & Lemieux, 2019; Li et al., 2024), the concept of an SME's digital footprint as a comprehensive and multifaceted signal of its credibility has not been systematically investigated. There is a need to move beyond analysing isolated digital datapoints to understanding how the aggregation of an SME's online activities, transaction histories, and digital presence collectively functions to reduce information asymmetry for lenders (Colombo, 2021).

2.7.4 Interplay Between Digital Signals and Traditional SME Credibility

The interaction between new digital signals (e.g., AI tool adoption, digital footprint) and traditional signals of SME credibility (e.g., managerial experience, business plans, collateral) is not well understood (Colombo, 2021). It remains unclear whether digital signals substitute for, complement, or moderate the effect of traditional credibility indicators in the loan approval process. Research is needed to determine if, for instance, a strong digital presence can compensate for a lack of tangible assets in the eyes of South African lenders (Motta & Sharma, 2020).

2.7.5 Application of AI and Machine Learning in SME Credit Assessment in Africa

There is limited empirical evidence on the application and effectiveness of AI and machine learning in assessing SME credit risk, specifically within Africa (Belhadi et al., 2025; Mhlanga, 2021). While the potential is acknowledged, practical implementation and its direct impact on loan approvals for local SMEs require empirical validation. The development of AI credit scoring models is often treated as a "black box".

Research is needed to unpack which specific digital data points (digital footprints) are most predictive of SME success and how their inclusion influences lending decisions for an otherwise underserved population (Bryan et al., 2024; Li et al., 2024).

2.8 Conceptual Model

Based on the established gaps in research, the conceptual model seeks to address the contextual details of SME financing in South Africa, and further, the demand-side dimensions of digital transformation. The conceptual model (Figure 2.1) below attempts to fill in this gap by integrating constructs of SME digital footprint, AI tool adoption, and traditional credibility signals to investigate the relationship and interaction effects on formal access to finance, such as loans. The model sought to address the need for a holistic understanding of how digital signals can function as a strategic driver for SMEs to mitigate information asymmetry and enhance creditworthiness. By incorporating both emerging digital metrics and established credibility factors, the model aims to provide a comprehensive framework for assessing SME financing potential in a South African context, where empirical evidence remains limited.

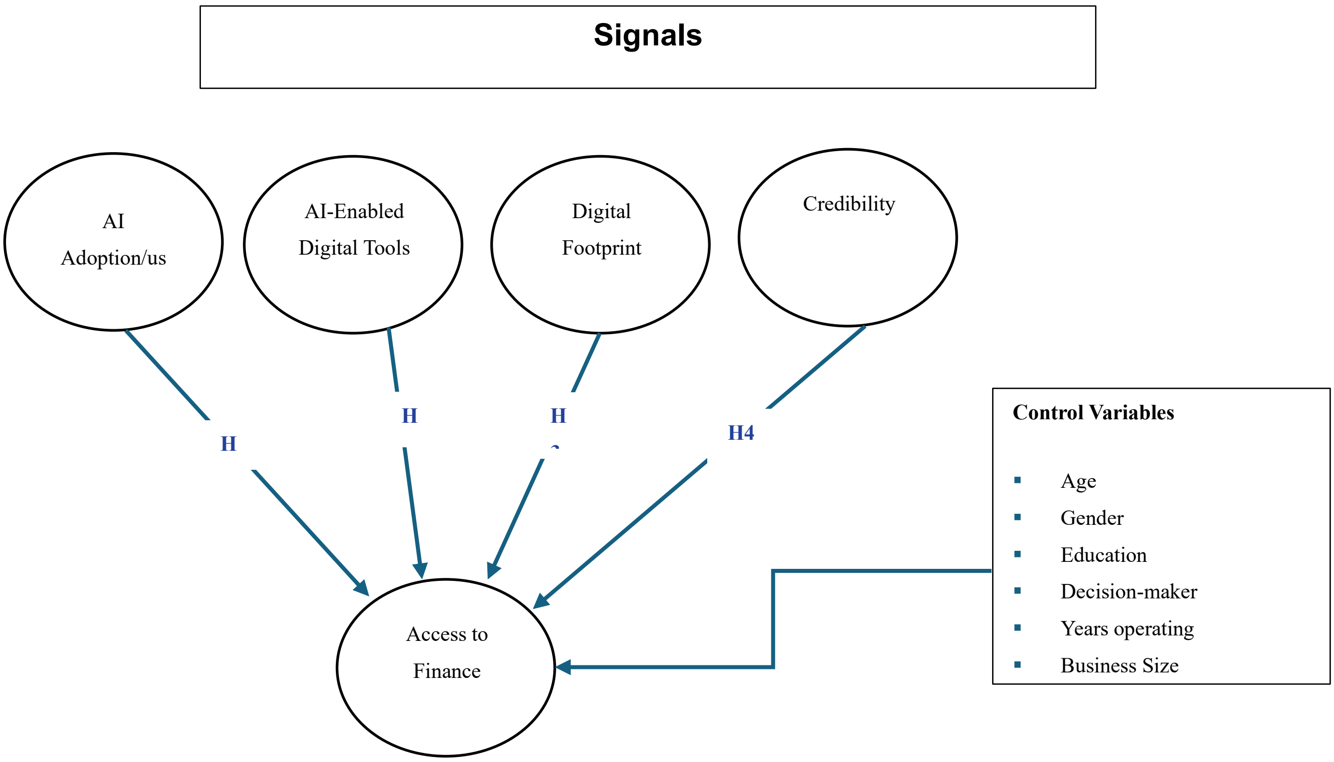

Figure 2.1: A Conceptual Model of the Relationship Between AI Adoption, Digital Transformation, Digital Footprints, Credibility and Access to Finance

Researcher's compilation (2025)

2.9 Conclusion

This chapter commenced with the SME definitions and South Africa's funding landscape. It then presented a review of relevant literature on the relationship between SME digital footprint, AI tool adoption, and traditional credibility signals and access to finance in the form of loan approval. The chapter further discussed information asymmetry, signalling theory, traditional signals and new signalling mechanisms. The chapter also presented empirical findings on the global and South African context, the role of technology in addressing financing constraints, and the trends and drivers of AI-enabled tool adoption in SMEs. Furthermore, barriers and enablers of AI adoption were discussed. Finally, the research gaps were explicitly summarised, and a conceptual model was presented. The next chapter presents the research hypotheses tested in the analysis towards the research objectives.

Chapter 3: Research and Hypotheses

3.1 Introduction

This chapter presents the research hypotheses, based on the research objectives of this study.

3.2 Research Objectives

Research objective 1: To examine the relationship between SME financial and nonfinancial signals (e.g., digital footprints, AI adoption, credibility) and their ability to secure financing.

Research objective 2: To identify which signals presented by SMEs are most strongly associated with positive financing outcomes.

Research objective 3: To contribute to signalling theory by testing the role of nonfinancial, technology-enabled signals as credible indicators of SME creditworthiness in an emerging market context.

3.3 Research Hypotheses

Based on the above-mentioned research objectives, the research hypotheses are formulated as follows:

H1: SMEs with higher levels of AI-enabled digital tool adoption are more likely to access finance.

H2: SMEs with stronger digital footprints are more likely to access finance.

H3: SMEs with higher credibility are more likely to access finance.

H4: The adoption of AI-enabled digital tools moderates the relationship between SME credibility and access to finance.

3.4 Linking Research Objectives and Hypotheses

Objective 1 & H1: Relationship Between SME Signals (Financial and Nonfinancial) and Securing Financing

The literature strongly supports the idea that SMEs use various signals to mitigate information asymmetry and secure financing (Connelly et al., 2011; Spence, 2002). Lenders face challenges in assessing the creditworthiness of SMEs due to informational opacity and a lack of traditional financial records (Guo et al., 2024; Kinyua et al., 2025; Sharma & Sharma, 2024). Consequently, SMEs must actively signal their quality and financial attractiveness to receive credit (Aktekin et al., 2018).

Traditional Financial Signals: Traditional signals include tangible assets used as collateral, audited financial statements, and a strong track record (Motta & Sharma, 2020; Watson & Wilson, 2002). For example, externally audited financial statements can enhance a firm's credibility, reducing financing hurdles (Kinyua et al., 2025).

Nonfinancial Signals (Emerging Area): The literature is increasingly recognising nonfinancial signals. AI adoption and a firm's digital footprint are emerging as critical non-traditional signals (Colombo, 2021; Rao et al., 2023). For instance, Aktekin et al. (2018) distinguish between intended signals (like a diverse financing portfolio) and unintended signals (like operational volatility), both of which affect a venture's financial attractiveness. This aligns with the research objective to examine a mix of financial and nonfinancial signals.

Objective 2 & H2a/H2b/H2c: Identifying the Most Influential Signals (Digital Footprints, AI Adoption vs. Traditional Signals)

The sources suggest a significant shift toward technology-enabled, nonfinancial signals, which may be more predictive than traditional ones, especially for SMEs that lack conventional credit histories.

H2a (Digital Footprints): The concept of a "digital footprint" as a credible signal is strongly supported. FinTech lenders and innovative banks are leveraging alternative data, often referred to as "weak signals" or digital footprints, to assess creditworthiness beyond traditional FICO scores (Jagtiani & Lemieux, 2019; Li et al., 2024). These footprints can include transaction histories, social media activity, and other online behaviours (Li et al., 2024; Mushtaq, 2022). Huang et al. (2025) have even proposed a framework for a "Digitisation Footprint" to assess digital efforts, indicating a move toward formalising this concept. The digitalisation of banks allows them to leverage these unique digital footprints to alleviate information asymmetry and ease financing constraints for companies with few tangible assets (Yang et al., 2025).

H2b (AI Adoption): While no literature directly tests SME adoption of AI tools as a signal for loans, the literature strongly implies its importance. The adoption of digital technologies by an SME is seen as a sign of its willingness to innovate, making it less likely to face financial constraints (Mushtaq et al., 2022). The digital transformation of an SME can improve its information disclosure, profitability, and risk resilience, thereby alleviating financing constraints from the capital demand side (Guo et al., 2024; Jeza & Lekhanya, 2022). Furthermore, lenders themselves are rapidly adopting AI to improve credit scoring, suggesting they value digital sophistication (Belhadi et al., 2025; Hassan, 2024; Mhlanga, 2021). An SME that adopts AI tools is thus likely signalling its alignment with modern, data-driven business practices valued by lenders.

H2c (Traditional vs. Nonfinancial Signals): The sources provide compelling evidence that traditional financial signals are becoming less predictive. Jagtiani and Lemieux (2019) found that the correlation between LendingClub's rating grades and borrowers' FICO scores dropped dramatically over time, indicating an increased reliance on alternative data. Li et al. (2024) show that AI-enabled credit scoring using weak signals (digital footprints) enhanced financial inclusion for an underserved population that lacked strong traditional credit histories. This suggests that for SMEs, which often lack the extensive financial records and collateral of large firms, nonfinancial digital signals could be more predictive and crucial for securing loans (Baloyi & Khanyile, 2022; Sharma & Sharma, 2024).

Objective 3 & H3: Extending Signalling Theory with Technology-Enabled Signals

Literature strongly supports the extension of signalling theory into the digital realm. Traditional signalling theory has been widely applied to SME financing (Rao et al., 2023), but there is a clear trend toward examining new and innovative signals (Colombo, 2021).

Moderation Role of Technology-Enabled Signals: The hypothesis that technology-enabled signals (digital footprints and AI adoption) moderate the relationship between SME credibility and financing outcomes is a novel and logical extension of the existing literature. Lenders use signals to infer unobservable firm quality or credibility (Connelly et al., 2011; Spence, 2002). The adoption of digital technologies and the resulting digital footprint serve as powerful, observable signals of an SME's underlying quality, such as its innovativeness, managerial competence, and transparency (Guo et al., 2024; Mushtaq et al., 2022). For example, AI-enabled tools can improve the quality of a firm's information disclosure, which in turn alleviates financing constraints (Guo et al., 2024). This process, where a digital action (e.g., AI adoption) leads to an improved signal (e.g., better disclosure) that results in a positive outcome (e.g., financing), is the essence of a mediation effect. Therefore, the study is well-positioned to formalise and test this relationship empirically.

Chapter 4: Research Methodology

4.1 Introduction

This chapter outlines the methodological approach employed to investigate the influence of AI-enabled tool adoption, digital footprints, and SME credibility on loan approval outcomes among South African SMEs. The research design follows Saunders and Lewis's (2018) research onion framework, systematically addressing each methodological layer from the philosophical framework to data collection and analysis procedures.

The chapter systematically addresses population and sampling from (Section 4.3–4.5); measurement instrument development and validation are covered in Sections 4.6–4.9, while data collection procedures (Section 4.7), and analytical techniques, including EFA, CFA and hypothesis testing are discussed in Sections 4.10–4.13.

Data quality controls and study limitations are acknowledged to ensure transparency and appropriate interpretation of results in Sections 4.14–4.15.

4.2 Research Design

Selecting a suitable research design is an important step in the research process because it involves posing questions, collecting data, and presenting the results (Saunders & Lewis, 2018). The research onion provides a structured approach to this process, metaphorically describing layers from the outer layer of philosophy to the inner layer where data collection and analysis conclude the process (Saunders & Lewis, 2018). These layers were covered in detail in the next sections, particularly with relation to examining the signals; AI-enabled tool adoption, digital footprints, and SME credibility, and their influence on loan approval outcomes among South African SMEs.

4.3 Research Philosophy

The study was grounded in an objectivist epistemology, which assumes that reality exists independently of human perception and can be understood through observation and measurement (Alvarez & Barney, 2010). From this epistemological stance, "the positivist research philosophy was adopted for this study, as it employs structured methods that facilitate replication and result in law-like generalisations" (Saunders & Lewis, 2018, p. 107).

This philosophical approach aligned with the study's aim to assess the measurable influence of AI-enabled tools, digital footprints, and SME credibility on loan approval outcomes, as it emphasises the formulation and testing of hypotheses through systematic and empirical methods. By quantifying these relationships, the study sought to generate empirical evidence on how such signals can enhance financial inclusion for South African SMEs (Oldemeyer et al., 2025).

4.3.1 Approach to Theory Development

This research followed a deductive approach to theory development, beginning with the established framework of signalling theory. Based on this theoretical lens, hypotheses were formulated to test the influence of AI-enabled tool adoption, digital footprints, and SME credibility on loan approval outcomes. The deductive approach was appropriate given the study's quantitative design and its aim to validate theoretical propositions empirically (Alvarez & Barney, 2010).

4.3.2 Research Strategy

The research process followed an established overall strategy to handle research questions and objectives. According to Saunders & Lewis (2018), a research strategy represents the main approach which guides researchers to find solutions for their research questions and objectives. The research study collected primary data through surveys from relevant respondents (SMEs). The survey questions were in a structured questionnaire and allowed respondents to respond independently while the researcher maintained complete non-interference.

4.3.3 Time Horizon

The cross-sectional study was employed to capture data from entrepreneurs at one time, primarily because SMEs in developing countries generally do not file detailed financial reports, limiting the availability of financial data needed for sophisticated longitudinal analysis (Quartey et al., 2017). This approach was also appropriate for investigating whether AI-enabled tool adoption, digital footprints, and SME credibility influence loan application outcomes for South African SMEs, particularly given the practical constraints associated with data collection in this sector and the specific nature of the variables being examined. What is also worth noting is that cross-sectional data are generally used to interpret results as an association that may suggest a possible underlying causal relationship, rather than definitively establishing causality (Motta & Sharma, 2020).

4.3.4 Choice of Methodology

This study adopted a mono method in the form of a quantitative approach to analyse the relationships between three independent variables: AI Technology tool adoption, digital footprint, perceived SME credibility, and the outcome, which leads to loan approval (dependent variable). These constructs required quantitative measurement because AI adoption levels exist on a continuous scale, which needs scaled measurement, while digital footprints have countable elements such as the number of platforms and transaction volumes, and credibility comprises multiple measurable dimensions (financial transparency, operational track record) and loan approvals function as binary outcomes appropriate for logistic modelling.

Quantitative methods are necessary for this study as they allow the measurement of levels of adoption from different aspects, testing hypotheses statistically, and separating individual variables after controlling for other factors such as business size, industry, or financial history (Arroyabe et al., 2024).

4.4 Population

In research, the term population represents the entire group of individuals or entities sharing common characteristics pertinent to a specific study. Scholars define a population as the complete set of elements, be it people, organisations, or events, that embody the traits under investigation (Creswell, 2017). When researchers study small and medium enterprises (SME), the respondents usually include owners, managers, or decision-makers, who participate in operational and strategic activities, especially relating to adopting technology and making financial decisions (Mhlanga, 2021).

According to the Small Enterprise Development Agency (SEDA,2023), the total number of SME owners in South Africa as of 2022 (Quarter 3) amounted to 2.68 million. And represent a significant portion of the business landscape, where they account for over 98,5% of all businesses in South Africa (McKinsey, 2020).

It is for that reason that the population for this study was owners and managers of SMEs, as they are critical respondents. Furthermore, they are directly engaged in decision-making processes and can provide first-hand insights into what AI technology is adopted and its subsequent effects on their financial accessibility (Arroyabe et al., 2024)

4.5 Unit of Analysis

The unit of analysis for this study was the individual SME owners within the context of the selected population in South Africa. The research concentrated on the collection and examination of data pertinent to these entities.

The choice of this unit of analysis was appropriate as it aligned with the research objectives and the nature of the data being collected. It also allowed for a detailed exploration of their perspectives and insights (Edmondson & McManus, 2007).

4.6 Sampling Method and Size

Small enterprises in the post-startup phase are typically those that have been in operation for approximately three to five years and have moved beyond the initial establishment stage, having survived the early challenges of startup life, but have not yet reached full maturity. On the other hand, medium enterprises have been operating for 5–10 years or above and are generally more established. Both these categories of entrepreneurs were selected at random using a probability sampling technique, giving them an equal opportunity of being included in the research. Random selection of the SMEs helped the researcher reduce selection bias and guarantee the objectivity and dependability of the gathered data (Cavusgil & Das, 1997). Additionally, these categorisations coincide with the descriptions provided in the National Small Enterprise Amendment Bill, as well as with the SME landscape as compiled by Statistics South Africa (Stats SA, 2024).

According to Andrade (2020), researchers often adopt a sample size between 100 and 200 respondents as a practical and ethical standard. Initially, the plan was to confine the study to SME owners and managers who have completed entrepreneurial development training at the GIBS Entrepreneurship Development Academy nationally, which comprised about 510 potential respondents. Following a low response rate from these potential respondents, the survey link was shared with multiple business groups on WhatsApp, where business size and sector characteristics are relatively consistent across the population.

4.7 Measurement Instrument

The measurement instrument, provided in Appendix B, was a survey questionnaire because it is a useful instrument in a quantitative study, as it includes all methods of data collection, which allows for the same set of questions to be asked to a large number of respondents (Saunders & Lewis, 2018).

The researcher employed an instrument that integrated items from validated measurement scales to enhance reliability and theoretical grounding. AI-enabled digital tool adoption items were adapted from the ICT Adoption Scale for SMEs and Digital Marketing Orientation scale (Özşahin et al., 2022); SME credibility items were drawn from the corporate credibility scale (Del Carmen & Lamelas, 2011); digital footprint strength items were drawn from a combination of validated digital-marketing items (Mahmutović, 2021; Özşahin et al., 2022). Unless otherwise specified, responses were recorded on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Refer to Appendix B for the questionnaire.

The design of the questionnaire included items that captured all constructs and perceptions related to signalling and information asymmetry, in alignment with the study's theoretical framework and hypotheses. Additionally, the design of the questionnaire included questions that were clear and could be easily understood, to ensure that the respondents could complete the questionnaire seamlessly. The benefit of the questionnaire is its reliability because it is anonymous, encourages honesty, and is inexpensive (Cohen et al., 2017).

4.8 Data Gathering Process

The data gathering process was preceded by an ethical clearance through the Gordon Institute of Business Science's Ethics Committee. Ethical considerations were paramount throughout this process, ensuring that respondents' confidentiality was respected and informed consent was obtained. For the second phase of the data gathering process, the researcher piloted the questionnaire via a Google link with eight owners of SMEs for a week, starting 18 August 2025, with the aim of troubleshooting any problems that respondents may experience when answering the questionnaire and adjusting prior to launching the main questionnaire. Minor changes were made to the questionnaire based on the feedback received. Questions that needed further explanation were expanded on to ensure clarity.

The next phase adopted Chidlow et al.'s (2015) rigorous data-collection process, where they posit the importance of thorough and precise data-collection procedures to ensure the reliability of the research and minimise non-response bias. This meant implementing a structured data collection process that included multiple contacts with potential respondents. For instance, a pre-notice message, followed by the survey, reminder and follow-up messages were sent using email and WhatsApp platforms to increase response rates, and the survey was kept open for longer than originally planned to ensure adequate sample representation and data quality.

It is important to note that while pilot study data is generally not included in final analyses, it was included for this study as the instrument was not materially changed/modified, and the sample is fully representative. Such practices are consistent with the methodological literature, such as Rao et al., (2023); Zhang et al., 2025), which advocate the need for a pilot study to improve the quality and credibility of survey-based research.

The questionnaire comprised six sections, namely:

Section 1: Demographic profiling

Section 2: Digital tool adoption

Section 3: SME Credibility

Section 4: Digital footprint

Section 5: Use of AI tools

Section 6: Access to finance (Loan approval)

4.9 Validity of the Questionnaire

The study's questionnaire was tested for accuracy in measuring the constructs of AI tool adoption, digital footprint, and SME credibility. Content validity was established using validated scales such as the ICT Adoption Scale for SMEs (Özşahin et al., 2022), the corporate credibility scale (Del Carmen & Lamelas, 2011), and the digital marketing orientation scale (Mahmutović, 2021; Özşahin et al., 2022).

The pilot study with eight SME owners confirmed adequate coverage of the intended domains and provided initial feedback on item clarity and relevance. Construct validity was evaluated through Exploratory Factor Analysis (EFA), which was performed using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy gauge in the JAMOVI software.

These tests were performed in collaboration with a statistician who reviewed the contents of the questionnaire and recommended corrections and amendments to item wording prior to ethical clearance approval.

4.10 Scale Reliability of the Measurement Instrument

Internal consistency reliability was assessed for each multi-item composite scale using Cronbach's alpha coefficient, a widely accepted statistical measure that estimates the extent to which items within a scale consistently measure the same underlying construct (Hair et al., 2021). Cronbach's alpha was calculated using JAMOVI software for the three composite scales: AI-enabled tool adoption (AIA), SME credibility (CRE), and digital footprint (DFP). To thoroughly evaluate scale reliability, the researcher examined not only the overall Cronbach's alpha for each construct but also conducted item-total statistics analysis. This involved computing "alpha if item deleted" values, which indicate what the alpha coefficient would be if each individual item were removed from the scale (Field, 2013). This analysis helps identify problematic items that may be weakening the overall scale consistency.

The decision-making process for item retention followed a balanced approach that considered both statistical evidence and theoretical relevance. Whilst items that substantially lowered alpha coefficients were flagged for scrutiny, removal decisions were not based solely on statistical criteria. Instead, the researcher evaluated whether items were conceptually essential to the construct, whether they contributed to content validity, and whether their behaviour in the EFA supported their retention (Hair et al., 2019). This approach ensured that scale refinement decisions were theoretically justified rather than purely data-driven.

For constructs achieving acceptable or excellent reliability (α ≥ .70), composite scores were computed by averaging item responses within each scale, after confirming that all items were coded in the same direction (higher scores indicating more of the construct). Where required for model comparability in subsequent analyses, standardised z-scores were calculated for each composite scale (Saunders & Lewis, 2018). This methodological approach to reliability testing ensured that the measurement instrument consistently captured the intended constructs across respondents, providing a solid foundation for subsequent hypothesis testing.

4.11 Data Analysis

The cleaning of the data, data processing and finally statistical data analysis were done using SPSS and JASP, respectively, because the latest version of SPSS does not have the Bayesian module for logistic regression. Descriptive statistics were conducted at the outset, covering the control variables such as the size and age of the firm, sector and location (to name a few). This was followed by tests of reliability, Cronbach's alpha with a threshold of 0.70 or higher, indicating acceptable internal consistency of the measurement scales (Tang et al., 2014).

Additionally, the researcher conducted an EFA to examine the underlying factor structure of the scales, ensuring that items are grouped under intended constructs.

Table 4.1: Hypotheses, Independent Variables, and Corresponding Statistical Tests

Hypothesis	Independent Variable(s)	Type of Analysis
H1	AI Adoption (continuous)	**Bayesian Binary Logistic Regression**
H2	Digital Footprint Strength (continuous)	**Bayesian Binary Logistic Regression**
H3	SME Credibility (continuous)	**Bayesian Binary Logistic Regression**
H4	SME Credibility, AI Adoption, and Interaction Term (all continuous)	**Bayesian Binary Logistic Regression with Interaction Term**

Researcher’s compilation (2025)

To test the study's hypotheses, the researcher employed the Bayesian inferential framework to enhance the generalisability of results (Table 4.1). Bayesian frameworks are suitable even when non-probability sampling is used because p-values have no meaning when a non-probability sampling technique is employed (Lukman et al., 2021). Accordingly, Bayesian binary logistic regression is appropriate because the study employed purposive sampling, and the dependent variable (access to finance) is binary (Yes/No) (Lukman et al., 2021).

For Hypothesis 1, a Bayesian binary logistic regression model with one predictor was employed, allowing the robust estimation of the probability of loan approval (access to finance) (Lukman et al., 2021). For Hypothesis 2, Bayesian binary logistic regression was also employed to determine whether SMEs with stronger online presence have higher odds of securing formal loans (Lukman et al., 2021). To test Hypothesis 3, which evaluated the influence of SME credibility on the likelihood of loan approval, Bayesian binary logistic regression was again appropriate to utilise, given the binary nature of the outcome variable and the continuous credibility scores as predictors (Lukman et al., 2021).

For Hypothesis 4, a moderation analysis using Bayesian binary logistic regression was conducted (Lukman et al., 2021). This hypothesis was based on the idea that AI adoption may strengthen the relationship between SME credibility and access to finance, acting as a moderating factor that boosts how much a credible reputation influences lenders' decisions. The model included an interaction term between mean-centred AI adoption and SME credibility to reduce multicollinearity and improve interpretability (Almquist et al., 2020). This helped to assess whether the relationship between credibility and access to finance changes depending on the level of AI adoption (Lukman et al., 2021).

4.12 Exploratory Factor Analysis

To assess data suitability for EFA, Bartlett's test of sphericity was conducted to determine whether the correlation matrix exhibited sufficient patterning for factor extraction, with statistical significance ($p < .001$) indicating factorability (Field, 2013).

The underlying factor structure of the measurement scales and assess whether items clustered into theoretically meaningful constructs was also examined through the EFA (Hair et al., 2019; Watkins, 2018). EFA served three primary purposes: (1)

checking dimensionality to confirm whether the theoretically proposed three-factor structure emerged empirically; (2) informing item retention decisions; and (3) supporting construct validity before confirmatory analyses (Worthington & Whittaker, 2006).

4.13 Confirmatory Factor Analysis

Following exploratory factor analysis, confirmatory factor analysis (CFA) was conducted to validate the measurement model and assess whether the theoretically proposed three-factor structure (AI-enabled tool adoption, digital footprint, and SME credibility) adequately fitted the observed data (Kline, 2023). Unlike EFA, which explores underlying factor structures, CFA tests a priori hypotheses about the relationships between observed variables and latent constructs, aligning with the study's deductive research design (Xia & Yang, 2019). CFA was performed using JAMOVI software with robust maximum likelihood estimation (MLR) to account for potential non-normality in the Likert-scale data (Shi et al., 2021). The measurement model specified three correlated latent constructs, each measured by their respective six indicators identified in EFA, with all factor loadings freely estimated and error variances constrained to be positive.

Construct validity was assessed through multiple criteria. Convergent validity was evaluated using standardised factor loadings (≥ .50, ideally ≥ .70), average variance extracted (AVE ≥ .50), and composite reliability (CR ≥ .70), following established guidelines (Hair et al., 2021).

Discriminant validity was assessed using two methods: the Fornell-Larcker criterion, which requires that the square root of each construct's average variance extracted (AVE) exceeds its correlations with other constructs; and the more stringent heterotrait-monotrait ratio of correlations (HTMT), which requires a threshold of HTMT < .85, offering a more robust assessment of discriminant validity (Franke & Sarstedt, 2019; Rönkkö & Cho, 2022). These assessments ensured that the measurement instrument accurately captured distinct yet theoretically related constructs before proceeding to structural model testing.

4.13.1 Model Goodness of Fit Tests

Model goodness-of-fit was assessed using multiple indices to comprehensively evaluate model adequacy, as reliance on a single index can be misleading (Hu & Bentler, 1999; Shi et al., 2019). The chi-square test statistic (χ^2) was reported for transparency, though it is sensitive to sample size and often rejects well-fitting models in large samples (McNeish et al., 2018). Therefore, additional fit indices less susceptible to sample size effects were prioritised. Absolute fit indices included the Root Mean Square Error of Approximation (RMSEA; acceptable ≤ .08, good ≤ .06) with its 90% confidence interval, and the Standardised Root Mean Square Residual (SRMR ≤ .08), which represents the average standardised residual correlation (Browne & Cudeck, 1992; MacCallum et al., 1996). Incremental fit indices included the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI), both with acceptable fit ≥ .90 and good fit ≥ .95 (Hu & Bentler, 1999; Marsh et al., 2004).

Model fit was evaluated holistically rather than relying on rigid cutoff criteria, acknowledging that fit indices should be interpreted in the context of model characteristics, sample size, and theoretical justification (Marsh et al., 2004; McNeish et al., 2018). A model was considered to demonstrate adequate fit if the majority of indices met their respective criteria and the specified structure was theoretically defensible (Kline, 2023). Recent research suggests that for models with strong theoretical grounding, slightly relaxed cutoffs (e.g., CFI/TLI ≥ .90) may be acceptable when other indicators support model adequacy (Shi et al., 2019). In cases where modification indices suggested model re-specification, changes were only implemented if they were theoretically meaningful and did not constitute post-hoc data dredging (Hermida, 2015). The final model balanced statistical fit with theoretical coherence, parsimony, and interpretability.

4.14 Data Quality Controls

To guarantee the validity and reliability of the research results, several quality control measures were implemented. Data cleaning was done during the study to find and fix problems such as outliers and missing data, which are critical for maintaining the integrity of the research results.

Descriptive statistics aided the researcher in summarising key characteristics of the dataset, including measures of central tendency and dispersion (Almquist et al., 2020). Internal consistency of the survey items was evaluated by reliability analysis, applying Cronbach's alpha of 0.7. Other validity tests, such as content validity evaluations and factor analysis, were implemented to guarantee that the intended constructs are fairly reflected. Furthermore, statistical assumptions testing confirmed that the data satisfy the criteria for particular statistical tests, including checks for homoscedasticity, linearity, normalcy, and independence of observations.

Post-analysis quality controls included verification of results by re-running analyses to check for consistency and cross-verifying with different statistical software. The robustness of the results to variations in data or the technique of analysis was evaluated by sensitivity analysis. Documentation and transparency were maintained by recording all steps, decisions, and methodologies used in the analysis, ensuring this documentation was available for review (Köhler et al., 2017).

4.15 Limitations

This study presents several limitations that should be acknowledged when interpreting the results. Firstly, the cross-sectional design is employed, meaning that data were collected at one moment in time. Although useful for the detection of AI adoption and its relationship with financial inclusion, this approach is by nature incapable of determining causality. A longitudinal approach would be more appropriate for studying the formation of these relationships over time (Hassan, 2024)

Secondly, as Podsakoff et al. (2003) state, the use of self-reported referents for the main variables (e.g. AI adoption, financial performance, loan approval) raises potential biases, including social desirability and recall bias. These biases may lead to inaccurate and biased data obtained (Podsakoff et al., 2003).

Additionally, the study utilised binary logistic regression for testing Hypotheses 1 and 2, which assumed that the relationship between the log-odds of the dependent variable and the independent variables is linear. Departures from this assumption and collinearity reduce the predictive validity of the model. Secondly, logistic regression fails to control for unobserved heterogeneity across SMEs that might spill over into financial performance (Hosmer et al., 2013).

The complexity of moderation analyses is another limitation. Caution is advised in the interpretation of these analyses, and the sample size needs to be sufficient to detect interaction and indirect effects. Type I or Type II errors can result from misspecification or inadequate power (Aguinis et al., 2017).

Another drawback is that the development of the digital footprint measure is ongoing, and the existing one lacks a standardised and validated scale. This lack of skill could also impact the construct of Hypothesis 3 and the consistency of data with other studies (Huang et al., 2025).

Lastly, the research study focused solely on perspectives of SMEs, whilst excluding other important stakeholders such as financial institutions and technology providers that develop and implement AI solutions. For future studies, data from these varied groups will facilitate a comprehensive understanding of the implications of AI technology on SMEs' access to finance (Tarr, 2021).

4.16 Conclusion

This chapter presented the research methodology and design employed in this study to address the problem statement formulated and the research objectives. It discussed the choice of methodology, population, unit of analysis, sampling method, measurement instrument, data gathering process, the validity of the questionnaire, data analysis, data quality controls and the research limitations. The next chapter presents the results from the data analysis, including the interpretation of the statistical results.

Chapter 5: Results of the Study

5.1 Introduction

This chapter presents the quantitative results of the study, which examined the influence of AI-enabled tool adoption (AIA), digital footprints (DFP), and SME credibility (CRE) on loan approval outcomes among South African SMEs. The full dataset comprised N = 180 SMEs; however, the analysis is based on a sample of 89 SMEs that applied for loans in the past twelve months; 0 (44.9%) of these were approved, and 49 (55.1%) were declined. Section 5.2 presents the demographic characteristics of the full sample (N=180), consisting of 91 (non-loan applicants) and the loan applicant subsample of 89, providing context for the respondent profile and loan approval patterns across different demographic and business characteristics. Section 5.3 describes the study variables, including their types, roles, and composite formulation, clarifying how key constructs (AIA, CRE, DFP) were operationalised and measured. Section 5.4 reports scale reliability analysis using Cronbach's Alpha, confirming internal consistency of the measurement instruments. Section 5.5 provides EFA results, total variance and factor loadings. Section 5.6 provides descriptive statistics for the key predictor variables. Section 5.7 outlines the model assumptions and estimation settings for the Bayesian logistic regression analysis, including the decision rules used to evaluate the hypothesis support. Section 5.8 presents the hypothesis testing results, examining four hypotheses (H1–H4) through Bayesian logistic regression.

5.2 Demography

5.2.1 Frequencies of **Demographics of Respondents**

The full dataset comprised N = 180 SMEs, whose demographics are reported for descriptive context in Table 5.1. However, the inferential analysis in this chapter focuses on n=89 firms that applied for a loan within the reference period, as the research questions relate specifically to loan application outcomes. The study also reports demographics for this analytic subsample. Any additional exclusions (e.g., missing outcome or key predictors) are described to ensure transparency.

Given the modest size of the analytic subsample (n = 89) and the likelihood that some classical assumptions may only be approximately satisfied, models were estimated in a Bayesian framework. Bayesian inference provides full posterior uncertainty and allows weakly informative priors that stabilise estimation in smaller samples. This approach is widely recommended when sample sizes are limited or separation/collinearity may challenge frequentist estimation (Aktekin et al., 2018).

Table 5.1: Respondent Demographics by Role, Age Band, Gender, Education, Years Operating, Employees, Sector, Province, and Financial Decision-Maker *(N = 180)*

Category	Variable	Frequency (n)	Proportion (%)
Role	Owner	147	81.7
	Co-Owner	20	11.1
	Key decision maker	11	6.1
	None of the above	2	1.1
Age band	18–24 yrs	2	1.1
	25–34 yrs	46	25.6
	35–44 yrs	94	52.2
	45–54 yrs	36	20.0
	55+ yrs	2	1.1
Gender	Female	79	43.9
	Male	101	56.1
Education	Grade 10–11 (Incomplete Matric)	3	1.7
	Grade 12 / Matric (NQF 4)	30	16.7
	Certificate (NQF 5 – TVET)	33	18.3
	Diploma (NQF 6)	38	21.1
	Bachelor's Degree (NQF 7)	20	11.1
	Honours/Postgrad Dip (NQF 8)	26	14.4
	Master's / PhD (NQF 9–10)	30	16.7

Category	Variable	Frequency (n)	Proportion (%)
Years Operating	< 1 year	6	3.3
	1–2 years	14	7.8
	3–5 years	60	33.3
	6–10 years	66	36.7
	> 10 years	34	18.9
Employees	0 (Only owner)	33	18.3
	1–4 (Micro-enterprise)	56	31.1
	5–10 (Small enterprise)	70	38.9
	11–50 (Medium enterprise)	18	10.0
	51+ (Outside SMME definition)	3	1.7
Sector	Construction	29	16.1
	ICT	24	13.3
	Manufacturing	21	11.7
	Other	19	10.6
	Financial & Insurance Services	14	7.8
	Professional, Scientific & Technical Services	13	7.2
	Education & Training	10	5.6
	Accommodation & Food Services	9	5.0
	Arts, Entertainment & Recreation	8	4.4
	Wholesale & Retail Trade etc.	8	4.4

Category	Variable	Frequency (n)	Proportion (%)
Province (main base)	Gauteng	94	52.2
	Limpopo	25	13.9
	KwaZulu-Natal	19	10.6
	Western Cape	8	4.4
	Mpumalanga	6	3.3
	Eastern Cape	2	1.1
	Northern Cape	2	1.1
	Other/multiple provinces	24	13.3
Financial Decision-Maker	Business Owner	154	87.0
	Business Owner + Partner	8	4.5
	Finance Manager	5	2.8
	Business Partner	4	2.3
	Others (GM/Service Provider, etc.)	3	1.7

Note. Percentages are rounded to one decimal place and may not total exactly 100% due to rounding

Researcher's compilation (2025)

Table 5.1 demographic profiles frequency statistics results show that from the total one-hundred and eighty (n=180) responses completed, the majority of respondents were business owners (82%), followed by co-owners (11%) and key decision makers (6%), while a small portion *1%) indicated they were not owners or decision makers in the respective businesses. 52% of the respondents were aged 35–44 years, reflecting a middle-aged entrepreneurial group. The next largest group was aged between 25–34 years (25.6%), followed by 45–54 years (20%). There were very few respondents under the age of 25 years (1%) or over 55 years (1%).

In terms of gender, the sample was slightly male-dominated, with 56.1% of the respondents being male and 43% of the respondents being female. The respondents were relatively well-educated, with the highest proportions holding a Diploma (21%), Certificate (18.3%), Master's or PhD (17%) and Matric (16.7%). In terms of the years that the SME had been in operation, the majority had operated their businesses for 6–10 years (36.7%).

The majority of respondents operate with 5–10 employees (39%) or as micro-enterprises with 1–4 employees (31%). Nearly one in five businesses (18.3%) were sole-owner operations, while larger enterprises (11–50 employees) represented 10%. Only a small fraction (1.7%) employed more than 50 people, indicating that most respondents run smaller-scale ventures typical of the SMME sector.

The sectoral distribution showed that the sectors which were represented the most were in sectors of Construction (16.1%), ICT (13.3%), Manufacturing (11.7%), and other services (10.6%). Smaller proportions operated in financial services (7.8%), Professional services (7.2%), and Education and Training (5.6%). Sectors such as Accommodation, Arts, and Retail each accounted for between 4–5% of respondents.

Moreover, from a geographical and provincial distribution perspective, just over half of respondents were based in Gauteng (52.2%), followed by Limpopo (13.9%) and KwaZulu-Natal (10.6%). The remaining respondents were located in other provinces, with minor representation in the Western Cape (4.4%), Mpumalanga (3.3%), Eastern Cape (1.1%), and Northern Cape (1.1%). Lastly, business owners serve as the primary financial decision-makers in most cases (87%), smaller percentages involved business partners (4.5%), finance managers (2.8%), or other stakeholders (<3%).

5.2.2 Frequencies of Demographics – Loan applicants

From a total of 180 respondents, 89 respondents indicated that they had applied for a loan, and thus formed the subsample analysed in this section. Tables 5.2 to 5.9 present the distribution of key demographic and business characteristics among these respondents, based on loan application and approval status.

Table 5.2: Frequencies of Role

Role	Counts	% of Total	Cumulative %
Co-Owner	9	10.11%	10.11%
Key decision maker (e.g. Finance Manager, Sales Manager, Operations Manager, HR Manager, Investor)	4	4.49%	14.61%
Owner	76	85.39%	100.00%

Researcher’s compilation (2025)

Table 5.3: Frequencies of Age

Age Band	Counts	% of Total	Cumulative %
25–34 years old	26	29.21%	29.21%
35–44 years old	54	60.67%	89.89%
45–54 years old	9	10.11%	100.00%

Researcher’s compilation (2025)

Table 5.4: Frequencies of Gender

Gender	Counts	% of Total	Cumulative %
Female	28	31.46%	31.46%
Male	61	68.54%	100.00%

Researcher’s compilation (2025)

Table 5.5: Frequencies of Education

Education Level	Counts	% of Total	Cumulative %
Bachelor's Degree (NQF Level 7)	7	7.87%	7.87%
Certificate (NQF Level 5, e.g., TVET)	14	15.73%	23.60%
Diploma (NQF Level 6)	27	30.34%	53.93%
Grade 12 / Matric (NQF Level 4)	13	14.61%	68.54%
Honours / Postgrad Diploma (NQF Level 8)	9	10.11%	78.65%
Master's or PhD (NQF Level 9/10)	19	21.35%	100.00%

Researcher’s compilation (2025)

Table 5.6: Frequencies of Years Operating

Years Operating	Counts	% of Total	Cumulative %
Less than 1 year	3	3.37%	3.37%
1–2 years	9	10.11%	13.48%
3–5 years	25	28.09%	41.57%
6–10 years	34	38.20%	79.77%
More than 10 years	18	20.22%	100.00%

Researcher’s compilation (2025)

Table 5.7: Frequencies of Employees

Employees	Counts	% of Total	Cumulative %
0 (Only owner)	12	13.48%	13.48%
1–4 (Micro-enterprise)	24	26.97%	40.45%
11–50 (Medium enterprise)	11	12.36%	52.81%
5–10 (Small enterprise)	41	46.07%	98.88%
51+ (Outside SMME definition)	1	1.12%	100.00%

Source: Researcher's compilation (2025)

Table 5.8: Frequencies of Sector

Sector	Counts	% of Total	Cumulative %
Accommodation & Food Services	3	3.37%	3.37%
Administrative & Support Services	2	2.25%	5.62%
Arts, Entertainment & Recreation	3	3.37%	8.99%
Construction	21	21.60%	30.59%
Education & Training	5	5.62%	36.21%
Financial & Insurance Services	10	11.24%	47.45%
Information & Communication Technology (ICT)	13	14.61%	62.06%
Manufacturing	8	8.99%	71.05%
Other	6	6.74%	77.79%
Mining & Quarrying	3	3.37%	81.16%
Professional, Scientific & Technical Services	8	8.99%	90.15%
Wholesale & Retail Trade, Repair of Motor Vehicles, Motorcycles & Personal Goods	7	7.87%	100.00%

Source: Researcher's compilation (2025)

Table 5.9: Frequencies of Provinces

Province	Counts	% of Total	Cumulative %
Eastern Cape; Gauteng; KwaZulu-Natal	2	2.25%	2.25%
Free State	1	1.12%	3.37%
Free State; Gauteng; Limpopo; North West	2	2.25%	5.62%
Gauteng	46	51.69%	57.30%

Province	Counts	% of Total	Cumulative %
Gauteng; KwaZulu-Natal; Limpopo	7	7.87%	65.17%
Gauteng; Limpopo; Mpumalanga; North West	4	4.49%	69.66%
KwaZulu-Natal	7	7.87%	77.53%
Limpopo	16	17.98%	95.51%
Mpumalanga	2	2.25%	97.75%
Northern Cape	2	2.25%	100.00%

Source: Researcher’s compilation (2025)

Tables 5.2–5.9 indicate that of those who had applied for a loan (n = 89) in the past twelve months, about one-third (33–35%) were ultimately approved.

Table 5.10: Frequencies of Q33 Loan Approved

q33_Loan Approved	Counts	% of Total	Cumulative %
0	49	55.1%	55.1%
1	40	44.9%	100.0%

Source: Researcher’s compilation (2025)

As indicated in Table 5.10, 55.1% of the loan applications were not approved, while 44.9% were approved. Loan approval was highest among respondents with Bachelor's degrees or Postgraduate qualifications and those operating for more than ten years. Notably, medium-sized enterprises (11–50 employees) and firms in the Education and Training or KwaZulu-Natal province recorded the highest approval rates. The business owner remained the key financial decision-maker.

5.3 Description of study variables and composite formulation

Table 5.11 summarises all the key variables used in the study, including demographic, independent, dependent, and control variables. It distinguishes between the different data types, such as categorical, binary, and continuous variables, indicating how each was measured and analysed. Firstly, demographic variables (e.g. role, age, gender, education, years operating, employees, sector, and province) provide background information describing the sample. The dependent variable (DV), Loan Approved (Q33), represents whether respondents' loan applications were approved (0 = No; 1 = Yes). The independent variables (IVs), including AIA (Adoption), CRE (Credibility), and DFP (Digital Footprint), are composite measures capturing the study's main constructs, each calculated as the mean of several related survey items. Financial knowledge serves as a control variable, helping to account for respondents' understanding of financial concepts when interpreting outcomes. Overall, Table 5.11 clarifies the structure and analytical role of each variable, supporting transparency in how data were organised and interpreted in the statistical analysis.

Table **5.11: Study Variables (Types, Roles and Keys)**

Variable	**Type**	**Role**	**Notes / Composite Membership**
Role	Categorical	Control variables	Owner / Co-owner / Key Decision Maker
Age band	Categorical	Control variables	25–34; 35–44; 45–54
Gender	Categorical	Control variables	Female / Male
Education (NQF)	Categorical	Control variables	4 (Matric) to 10 (Master's/PhD)
Years operating	Categorical	Control variables	<1; 1–2; 3–5; 6–10; >10
Employees	Categorical	Control variables	Only owner; 1–4; 5–10; 11–50; 51+
Sector	Categorical	Control variables	e.g., Construction, ICT, Manufacturing, etc.
Province	Categorical	Demographic	e.g., Gauteng, KZN, Limpopo, etc.
Loan approved (Q33)	Binary (0/1)	DV	0 = No; 1 = Yes
AIA (Adoption)	Continuous	IV (Composite)	Mean of q12–q17 (digital adoption items)
CRE (Credibility)	Continuous	IV (Composite)	Mean of q18–q23 (credibility/trust items)
DFP (Digital Footprint)	Continuous	IV (Composite)	Mean of q24–q29 (website/social/online items)
AI tools adopted (q30)	Single item	IV	Low MSA; interpret with caution in EFA
Financial knowledge	Continuous	Control	fin_knowledge.1–7 (1–7 Likert scale)

Source: Researcher’s compilation (2025)

In this study, the composite scores were computed by averaging item responses within each construct (after checking item direction). The three composites below were formed and treated as continuous variables in subsequent analyses, with z-scores used where model comparability was required

(1) AIA (q12–17).

(2) CRE (q18–23).

(3) DFP (q24–29).

5.4 Scale Reliability

Internal consistency was assessed via Cronbach's Alpha (Table 5.12). AIA was acceptable (α to 0.703), with Alpha rising to .792 if q12 was removed; however, q12 was retained to preserve content coverage and because factor analysis (below) informs item decisions beyond Alpha.

The CRE and DFP scales demonstrated excellent reliability (α = 0.912 and 0.929, respectively), with no items requiring removal.

Table 5.12: Reliability Analysis of Scales

Scale	Items	Cronbach's Alpha (α)	Alpha if Deleted	Decision
AIA	q12–q17	α = 0.703 (acceptable)	q12.enterprise.sw → 0.792 (would increase), q13 → 0.675, q14 → 0.620, q15 → 0.582, q16 → 0.664, q17 → 0.609 (would decrease)	Keep all items
CRE	q18–q23	α = 0.912 (excellent)	Alpha if deleted ranges ≈ 0.895–0.911 (mostly lower)	Keep all items
DFP	q24–q29	α = 0.929 (excellent)	Dropping any item reduces α	Keep all items

Source: Researcher’s compilation (2025)

5.5 Exploratory Factor Analysis

Following the assessment of the statistical validity of constructs and analogous items, EFA was undertaken to assess the principal factor structure and designs under each construct. The KMO value of 0.650 indicated acceptable sampling adequacy for factor analysis, whilst Bartlett's test of sphericity (χ^2 (190) = 461.33, $p < .001$) confirmed that the correlation matrix was suitable for EFA (Field, 2013). The three-factor solution that emerged explained approximately ≈60.54% of the total variance, with items loading coherently onto their theoretically intended constructs, thereby supporting convergent validity (Hair et al., 2019).

Factor 1 reflected digital footprint/marketing (e.g., website activity, social presence, online performance metrics; strong loadings ≈ .71–.90).

Factor 2 captured credibility/trust and records (e.g., competence, honesty, trustworthiness; loadings ≈ .79–.88).

Factor 3 represented strategy/operations knowledge (e.g., digital strategy and operational planning; loadings ≈ .65–.77). Two design notes: (i) q12 (enterprise software) loaded on Factor 1 (~.60), indicating that enterprise-software use appears to function as a visible digital-maturity signal aligned with the footprint/marketing domain; and (ii) items q14–q17 aligned with Factors 2–3 (≈ .47–.77), consistent with their emphasis on capability/operations rather than pure AI adoption. Cross-loading items (q23, q30) and high-uniqueness items (q30, financial-knowledge) were flagged for measurement refinement; the three-factor interpretation remains theoretically coherent.

Results are thus presented in two sections. Section 5.5.1 presents the results of total variances explained per the extracted factor under each construct, and Section 5.5.2 presents factor loadings of variable items under each construct as presented below.

5.5.1 Total variance

The Factor Statistics table (Table 5.13) summarises the results of an exploratory factor analysis. Firstly, the SS Loadings (sums of squared loadings) show how much variance each factor explains. The % of Variance column indicates that Factor 1 explains about 24 % of the total variance, Factor 2 explains 19.9 %, and Factor 3 explains 16.6 %. Together, the three factors account for roughly 60.5 % of the total variance, suggesting these three latent factors capture most of the meaningful information in the dataset.

Table 5.13: Factor Statistics Summary

Factor	SS Loadings	% of Variance	Cumulative %
1	4.80877	24.04387	24.04387
2	3.97121	19.85603	43.89990
3	3.32779	16.63897	60.53888

Source: Researcher’s compilation (2025)

5.5.2 Factor loadings

Table 5.14: Exploratory Factor Loadings

Construct	Item	F1	F2	F3
Digital Footprint (DFP)	q24 Website active	0.82	-	-
	q25 Social active	0.74	-	-
	q26 Website interactive	0.85	-	-
	q27 Online perf metrics	0.90	-	-
	q28 Digital mkt plan	0.90	-	-
	q29 Digital mkt expertise	0.71	-	-
Credibility (CRE)	q18 Competence	-	0.85	-
	q19 Expertise	-	0.79	-
	q20 Trustworthiness	-	0.88	-
	q21 Honesty	-	0.88	-
	q22 Accounting records	-	0.69	-
	q23 Docs ready	0.42	0.42	-
AI-enabled tools (AIA)	q12 Enterprise SW	0.60		-
	q14 Supply chain IS	-	0.47	-
	q15 Digital strategy	-	0.77	-
	q16 Perf metrics (tools)	-	0.70	-
	q17 Digital ops plan	-	0.65	-
	fin_knowledge1_7	-	-	0.89

Source: Researcher’s compilation (2025)

5.6 Descriptive Analysis

Table 5.15 presents descriptive statistics for the three key predictor variables: AIA, CRE and DFP. Histogram inspection indicated that AIA was approximately symmetric around the mid-upper range. CRE clustered towards higher values, suggesting a slight negative skew, whereas DFP exhibited a broader dispersion. These observations guided later choices, for example, standardisation and robust checks (See histograms in Appendix F).

Table 5.15 confirms balanced outcome counts and sensible spreads on AIA, CRE, and DFP. This supports running logistic models and discussing effects on approval odds in the next sections.

Table 5.15: Descriptive Statistics for Key Composite

Variable	N	Mean	SD	Min	Max
AIA	89	3.597	0.719	1.333	4.667
CRE	89	4.266	0.667	1.000	5.000
DFP	89	3.479	1.011	1.000	5.000

Source: Researcher's compilation (2025)

5.7 Model Assumptions

Bayesian logistic regression models were estimated under default weakly-informative priors, using MCMC (Markov Chain Monte Carlo) with 5000 posterior samples and seed = 123 for reproducibility. The study reports Bayes factors (BF), posterior means of coefficients, and 95% credible intervals (CrI).

Assumption / Diagnostic	AIA Model	DFP Model	CRE Model	AIA × CRE (Interaction) Model
Data separation	No separation detected (balanced DV distribution 49/40).	No separation detected.	No separation detected.	No separation detected.
Linearity of logit	Approx. linear relationship visible in	Slight curvature; acceptable.	Adequate; no systematic pattern.	Adequate; no major pattern.

	residuals vs fitted plot.			
Multicollinearity	Not an issue (single predictor).	Not an issue (single predictor).	Not an issue (single predictor).	Checked via pairwise correlations; all < 0.7.
Outliers & influence	No extreme standardised residuals or leverage points.	None observed.	None observed.	None observed.
Posterior convergence	JASP does not expose R-hat/ESS; assumed adequate as model ran without warnings.	Same as AIA.	Same as AIA.	Same as AIA.
Prior sensitivity	Bayes Factors stable under default Cauchy priors.	Model evidence insensitive to priors.	Same result.	Stable under tested priors.
Posterior predictive fit	Good visual alignment in residual vs fitted and Q–Q plot.	Q–Q plot near normal; minor deviations acceptable.	Adequate posterior predictive fit.	Fit adequate; no systematic bias.
Model evidence (BF_{10})	12.20 → strong evidence vs null.	0.36 → weak evidence vs null.	2.35 → anecdotal evidence vs null.	3.94 → moderate evidence vs null.
R^2 (model fit)	0.077	0.002	0.043	0.085
Conclusion	Assumptions acceptable; strong model evidence.	Assumptions acceptable; model not supported.	Assumptions acceptable; limited evidence.	Assumptions acceptable; moderate support.

5.8 Inferential Statistics

5.8.1 Model Comparison: Single-Predictor Bayesian Regression

Table 5.16 compares each single-predictor model to the null model using Bayes Factors (BF_{10}), posterior model probabilities, and R^2 values. AIA showed strong evidence over the null (BF_{10} = 12.20), CRE showed anecdotal to moderate evidence (BF_{10} = 2.35), and DFP was not supported (BF_{10} = 0.36).

Table 5.16 also indicates balanced outcome counts and sensible spreads on AIA, CRE, and DFP. These results provide a foundation for running logistic regression models and examining their impact on loan approval odds, which was discussed in the following section.

Table 5.16: Model Comparison: Single-Predictor Bayesian Regression

Model	P(M|data)	BF_{10}	R^2	Evidence Summary
AIA vs Null	0.924	12.197	0.077	Strong evidence for the model
CRE vs Null	0.702	2.354	0.043	Anecdotal–moderate for model
DFP vs Null	0.264	0.358	0.002	Evidence favours null

Note. BF_{10} compares each predictor model to the intercept-only (null) model

Source: Researcher's compilation (2025)

5.8.2 Posterior Summaries (Single Predictors)

Table 5.17 presents posterior summaries for the coefficients of each single predictor. The 95% credible intervals for AIA, CRE, and DFP all included zero, indicating that the effect sizes were not estimated with decisive precision.

Table 5.17: Posterior Summaries of Coefficients (Single Predictors)

Predictor	Mean (log-odds)	SD	95% CrI: Lo	95% CrI: Hi
Intercept (AIA model)	3.053	1.528	-0.355	5.575
AIA	-0.748	0.369	-1.327	0.000

Intercept (CRE model)	2.376	2.301	-0.744	6.514
CRE	-0.437	0.419	-1.264	0.066
Intercept (DFP model)	-0.107	0.463	-0.805	1.158
DFP	-0.016	0.087	-0.242	0.167

Source: Researcher's compilation (2025)

Note. Odds ratios (OR) are obtained as exp (beta coefficient). CrIs including 0 indicate effects not estimated with decisive precision at the 95% level.

5.8.3 Interaction Model

Table 5.18 compares models that include the interaction between AIA and CRE. The full model (AIA + CRE + interaction) showed moderate evidence over the null (BF_{10} = 3.94). However, the interaction term's 95% credible interval included zero, indicating imprecision in the estimate. Table 5.19 provides posterior summaries for the interaction model coefficients. The interaction term (AIA × CRE) was not estimated with decisive precision, as its 95% credible interval included zero.

Table 5.18: Bayesian Logistic Regression Models Including Interaction Effects Between AIA and CRE

Model	P(M—data)	BF_{10}	R^2	Evidence summary
AIA + CRE + Interaction	0.244	3.938	0.085	Moderate vs null
Interaction only	0.147	7.093	0.066	Moderate–strong vs null
AIA only	0.252	12.197	0.077	Strong vs null
AIA + Interaction	0.096	4.633	0.077	Moderate vs null
AIA + CRE (no interaction)	0.091	4.396	0.077	Moderate vs null
CRE only	0.049	2.354	0.043	Anecdotal–moderate
CRE + Interaction	0.059	2.857	0.068	Anecdotal–moderate
Null	0.062	1.000	0.000	Reference

Note. The table presents model comparisons using posterior model probabilities (P(M—data)), Bayes Factors (BF_{10}), and R^2 values.

Source: Researcher’s compilation (2025)

Table 5.19: Posterior Summaries for Bayesian Logistic Regression Models Including Interaction Effects

Term	Mean (log-odds)	SD	95% CrI: Lo	95% CrI: Hi
Intercept	4.378	4.988	-2.229	17.360
AIA	-0.839	1.259	-4.463	0.723
CRE	-0.231	0.809	-2.587	1.042
AIA X CRE	0.055	0.264	-0.339	0.759

Note. The interaction's CrI includes 0; term-level precision is therefore not decisive at 95%.

Source: Researcher’s compilation (2025)

5.9 Hypothesis Testing

This study employed Bayesian logistic regression to test the hypotheses. Before presenting the results, it is important to define the key statistical terms and decision rules used in this analysis under Table 5.20 (Kass & Raftery, 1995).

Table 5.20: Key Statistical Terms and Definitions

Term	Description
Null model	A baseline with no predictors (intercept only). It assumes every firm has the same approval probability.
Bayes factor (BF_{10})	Indicates how much more the data support a model with a predictor versus the null. $BF_{10} > 1$ favours the predictor model; $BF_{10} < 1$ favours the null. Rules of thumb: 1–3 = anecdotal, 3–10 = moderate, 10–30 = strong evidence.
Credible interval (CrI)	A 95% CrI is the range of effect sizes most compatible with the data and priors. If it includes 0 (log-odds) or 1 (odds ratio), the effect is not precisely estimated at 95%.

Term	Description
Odds ratio (OR)	Obtained by exponentiating a coefficient. OR = 1: no change in odds; OR > 1: increases odds; OR < 1: decreases odds.

Source: Researcher's compilation (2025)

5.9.1 **Decision Rules**

The decision rules outlined below were pre-specified to ensure transparent and balanced interpretation of the evidence.

1. Supported: BF10 ≥ 3 and the 95% CrI for the focal term excludes 0.

2. Partially supported: BF10 ≥ 3 (model-level evidence vs null), but the 95% CrI for the focal term includes 0.

3. Not supported: BF10 < 3 (model-level evidence below threshold or favours null), regardless of the CrI.

The "partially supported" signals that the model with the predictor improves explanation over the null, yet the precise size of the effect remains uncertain at the 95% level. This is a balanced way to recognise evidence without overstating certainty.

5.9.2 H1: Adoption of AI-Enabled Tools (AIA) and Access to Finance

Model evidence: The model incorporating AIA-only demonstrates strong empirical support when compared to the null model, with a Bayes Factor of BF_{10} = 12.2., This indicates that the observed data are approximately twelve times more consistent with a model that includes a relationship between AIA and loan approval outcomes than with a baseline model that assumes no such relationship.

Coefficient precision: The 95% CrI for the AIA coefficient includes 0, so the exact size of the effect is not determined with decisive precision at the 95% level. While the direction of the effect may be suggestive, the statistical precision remains inconclusive (i.e. not significant).

In conclusion, the inclusion of AIA as a predictor makes a meaningful contribution to explaining variations in loan approval outcomes. However, the estimated effect size is accompanied by considerable uncertainty and should be interpreted with caution.

Verdict based on decision rules: Given that the Bayes Factor exceeds the threshold of 3 (BF≥ 3) and the credible interval (CrI) includes zero, the evidence is best characterised as partially supportive of a meaningful relationship between AIA and loan approval.

5.9.3 H2: Digital Footprint Strength (DFP) and Access to Finance

Model evidence: The model including DFP-only does not receive empirical support over the null model, as indicated by a Bayes Factor of BF_{10} = 0.36. This suggests that the data are more consistent with a model that excludes DFP than with one that posits a relationship between digital footprint and loan approval outcomes.

Coefficient precision: The 95% credible interval (CrI) for the DFP coefficient includes zero, indicating that the effect size is not estimated with sufficient precision to draw firm conclusions.

Verdict based on decision rules: Given that the Bayes Factor is below the threshold of 3 (BF < 3) and the credible interval includes zero, the evidence is best interpreted as not supportive of a meaningful relationship between DFP and loan approval. Within this sample, variations in digital footprint do not appear to be clearly associated with loan approval outcomes once statistical uncertainty is considered.

5.9.4 H3: SME credibility (CRE) and Access to Finance

Model evidence: The CRE-only model presents anecdotal to moderate evidence in favour of a relationship with loan approval outcomes, with a Bayes Factor of BF_{10} = 2.35. However, this value falls below the conventional threshold of 3, indicating that the evidence is not sufficiently strong to confidently favour the model over the null.

Coefficient precision: The 95% credible interval (CrI) for the CRE coefficient includes zero, suggesting that the effect size is not estimated with adequate precision to support definitive conclusions.

Verdict based on decision rules: There are indications of a potential relationship between credibility and loan approval, but the statistical evidence is not strong enough, and the estimate lacks the precision required to meet the study's criteria for support.

As the Bayes Factor is below 3 (BF < 3) and the credible interval includes zero, the evidence is considered not supportive of a reliable relationship between CRE and loan approval.

5.9.5 H4: Moderation by AIA of the CRE Approval Association

Model evidence: The full model, including AIA, CRE, and their interaction, demonstrated moderate evidence against the null model (BF10=3.94), indicating that the data are approximately four times more consistent with a model that includes the interaction term than with a baseline model that assumes no predictors.

Coefficient precision: The 95% CrI for the interaction includes 0, indicating imprecision in the specific moderation term. Considering AIA, CRE, and their interplay improves overall explanation relative to a flat baseline; however, the precise size of the interaction effect is uncertain at 95%.

Table 5.21 summarises the hypothesis testing outcomes based on the predefined decision rules. H1 and H4 were partially supported, while H2 and H3 were not supported.

Table 5.21: Summary of Hypothesis Support Based on Bayesian Model Comparison

Hypothesis	Evidence Summary (Short)	Verdict
H1 (AIA)	Strong model evidence vs baseline: coefficient CrI includes 0	Partially supported
H2 (DFP)	Favours baseline; coefficient CrI includes 0	Not supported
H3 (CRE)	Evidence below "moderate" threshold; coefficient CrI includes 0	Not supported
H4 (Moderation)	Full model outperforms baseline; interaction CrI includes 0	Partially supported

Source: Researcher’s compilation (2025)

5.10 Conclusion

This chapter presented results obtained from statistical analysis of primary data collected through a survey from owners, co-owners and decision-makers of SMEs. The results presented include frequencies of the demographic profiles of all respondents; however, the analysis focused on 89 loan applicants, after data cleaning and removal of incomplete responses.

The study employed Bayesian logistic regression to test the hypotheses, utilising weakly informative priors and Markov Chain Monte Carlo (MCMC) methods with 5,000 posterior samples. Evidence was evaluated using Bayes factors (BF_{10}) to compare predictor models against a null baseline, with 95% credible intervals (CrI) used to assess coefficient precision. A three-level decision framework was pre-specified: *supported* ($BF_{10} \geq 3$ and CrI excludes 0), *partially supported* ($BF_{10} \geq 3$ but CrI includes 0), and *not supported* ($BF_{10} < 3$).

This transparent framework allowed for balanced interpretation of evidence, acknowledging model-level improvements while remaining candid about parameter uncertainty. The results presented in this chapter form the empirical foundation for the discussion and theoretical implications presented in the following Chapter 6.

Chapter 6: Discussion of Results

6.1 Introduction

The study examined the influence of AI-enabled tool adoption (AIA), digital footprints (DFP) and SME credibility (CRE) on loan approval outcomes for 89 South African SMEs. An overview of the key results is presented below.

H1: SMEs with higher levels of AI-enabled digital tool adoption are more likely to access finance, which is **partially supported.** This is demonstrated by the strong model evidence (BF_{10} = 12.20), suggesting that lenders acknowledge that AI adoption improves the explanatory model. However, the 95% Credible Interval (CrI) includes zero, indicating imprecise coefficient estimates. Therefore, AI adoption may contribute to explaining approval variance, but not decisively.

H2: SMEs with stronger digital footprints are more likely to access finance, but this is **not supported,** as the model is not favoured over null (BF_{10} = 0.36), and CrI includes zero. These results suggest that public digital presence is not clearly associated with loan approval outcomes.

H3: SMEs with higher credibility are more likely to access finance, but this is **not supported**. This is due to the anecdotal-to-moderate evidence (BF_{10} = 2.35), which is below the threshold of 3, with CrI including zero. This suggests that while credibility emphasises governance and reputation, lenders prioritise debt-service capacity. So while credibility is directionally plausible, it is unsupported under the study's criteria.**H4:** The adoption of AI-enabled digital tools moderates the relationship between SME credibility and access to finance, which is **partially supported** due to the moderate model evidence (BF_{10} = 3.94), but with an imprecise moderation effect, as 95% CrI includes zero. This is in line with the rule BF_{10} ≥ 3.94 with CrI including zero. Suggesting that including the interaction of AI improves overall fit, but the exact size remains uncertain.

Overall, the pattern observed across the hypotheses suggests that digital signals hold relevance at the model level, indicating some degree of recognition by lenders. However, the imprecision at the parameter level reflects uncertainty regarding the specific magnitude and consistency of their contribution.

Detailed discussion and interpretation of Chapter 5 results follow in the next sections of the chapter, as follows: Sections 6.2–6.5 provide hypothesis-specific discussions linking results to literature. Section 6.6 establishes the theoretical interpretation framework through the signalling and information asymmetry theory; Section 6.7 synthesises control variable insights; and Section 6.8 draws a conclusion.

6.2 H1: The Relationship Between the Adoption of AI-Enabled Tools (AIA) and Access to Finance

The hypothesis was partially supported, as the model showed strong evidence (BF_{10} = 12.20) indicating data 12 times more consistent with the relationship than the null. This suggests that lenders acknowledge that AI adoption improves the explanatory model. This perspective is aligned with multiple studies, such as Mushtaq et al. (2022), who posit that SMEs with high ICT usage are less likely to experience financing constraints and that banks view ICT adoption as a positive signal of innovation willingness, enhancing perceived loan repayment capacity.

A view also shared by (Guo et al., 2024), who reported that digital transformation alleviates SME financing barriers, reduces information asymmetry between firms and financial institutions. In addition, the study by Mhlanga (2021) reports that AI and machine learning may overcome information asymmetry and enable access to finance for SMEs lacking traditional collateral, especially in emerging markets.

However, 95% CrI includes zero, indicating imprecise coefficient estimates, suggesting that it is unclear exactly how much AI adoption matters. The results showed that AI adoption may contribute to explaining approval variances, but not decisively. This view is also shared by Li et al. (2024), who reported that while the adoption of an AI model increased the approval rate for the underserved population and reduced the default rate, the overall approval rate did not change much for the whole population.

This ambiguity may, in part, be attributed to how AI adoption was measured. Specifically, the current measure captures the breadth of adoption, rather than the depth of adoption. The measure captures "which tools" are present, not how they are used, for example, invoicing automation, CRM integration, and fraud checks. The issue is that the survey measured which AI tools were adopted by SMEs, not how deeply integrated or how effectively they are used in their operations (surface adoption vs. embedded adoption) (Arroyabe et al., 2024).

Secondly, in credit assessments, lenders place greater weight on hard financial metrics such as cash flow stability, collateral, and repayment history (Li et al., 2024). While AI-enabled applications (AIA) may enhance operational efficiency, they alone are unlikely to secure loan approval (Li et al., 2024). Thirdly, the timing of the adoption must be considered, as recent adoption of AI and its benefits may lag and not be visible in the financial statements that lenders review (Guo et al., 2023). For example, a firm equipped with an AI-enabled bookkeeping system may still be denied a loan if its cash flows are volatile. While such tools can enhance operational efficiency, they do not substitute for core financial indicators as repayment capacity remains the primary determinant in loan approval decisions (Li et al., 2024).

6.3 H2: The Relationship Between Digital Footprint (DFP) and Access to Finance

The relationship between digital footprint and loan approval was not supported, as the model is not favoured over null (BF_{10} = 0.36), and CrI includes zero. Digital footprints (DFP), defined as nontraditional information sourced from online activities, mobile data, and company registries, are theoretically positioned as crucial new signals of creditworthiness, especially for light-asset enterprises lacking traditional collateral (Mhlanga, 2021; Zhang et al., 2025). The empirical rejection of H2 suggests that, as a standalone factor, the digital footprint signal is either not consistently utilised by lenders or lacks the necessary quality and completeness to reliably influence credit decisions in this context (Li et al., 2024). This view is also shared by Rao et al. (2023), who report that the aggregation of online activity alone failed to generate a credible, strong signal sufficient to mitigate information opacity.

These views contradict results by Yang et al. (2025), which reported that banks are progressively adopting digital footprints to mitigate information asymmetry, particularly effective for light-asset SMEs. Mhlanga (2021) reported that specialised FinTech lenders with proprietary algorithms and alternative data sources provide collateral-free loans in emerging markets such as Kenya, Nigeria, India and South Africa. Additionally, an empirical study by Jagtiani and Lemieux (2019) found that reliance on alternative data has increased over time. Furthermore, it is worth noting that most of the existing literature originates from developed markets such as the United States, Europe, and parts of Asia, where financial systems are more digitally advanced. In contrast, South Africa's traditional banking sector tends to be more conservative in its adoption of emerging technologies (Rao et al., 2023)

From a sector-specific perspective, digital footprint is likely more relevant to SMEs in sectors such as e-commerce, where online presence directly generates revenue; ICT/Software; professional services, whereby a firm's website and LinkedIn signal credibility, and hospitality, where online reviews are critical signals for potential customers. However, it might be less relevant for construction, manufacturing, wholesale/trade, where B2B relationships are more important than public visibility. The study sample sector composition is construction (16.1%), ICT (13.3%), and manufacturing (11.7%), followed by diverse others. Sector-specific analysis would likely reveal heterogeneity, as the sample size prohibits this.

These results are consistent with those reported by Guo et al. (2024), who reported that the positive mitigating effect of digital transformation, a proxy for leveraging digital footprint, is highly dependent on regional and firm characteristics, suggesting a non-positive or insignificant relationship in less developed contexts.

In addition, platform heterogeneity contributes to the weak signals of digital footprint because of the variety of digital footprints (i.e., website activity, social media presence, online measurements, and digital marketing. It is difficult to unify such diverse digital footprints into one score. It is in this broader context that the work of Li et al. (2024) falls short, as it deals with specialised FinTech contexts employing in-house developed algorithms to process different sources of weak signals independently. Since the DFP composite is made up of individual platforms with different characteristics, the different effects might have been obscured, making the digital footprint a poor predictor of loan acceptance. Overcoming this complexity and heterogeneity of digital footprints requires advanced analytical tools, strongly implying that a simplistic aggregation would be insufficient (Li et al., 2024).

As established in the theoretical framework, digital footprints are entirely public information; therefore, lenders prioritise private financial data that directly predicts payment capacity. In this study, 36.7% of the SMEs operated between 6 and 10 years and reported that their firm's private financial track records are available. As lenders rely on this private primary input, the public digital footprint is secondary, which explains the reason for the DFP showing no significant effect on loan approval.

From an African context, the non-significance reinforces nuanced challenges facing SMEs in emerging markets, particularly South Africa (Baloyi & Khanyile, 2022). At the same time, innovative financing options like mobile lending utilise digital footprints (Mhlanga, 2021); overall failure of DFP to predict access is rooted in fundamental contextual limitations. Due to resource constraints, digital divide and incomplete adoptions whereby tools are present but not optimally utilised, many SA SMEs have not yet fully assimilated digital technology, potentially compromising their ability to generate effective or extensive digital signals lenders can use and trust (Jeza & Lekhanya, 2022).

6.4 H3: The Relationship Between SME Credibility (CRE) and Access to Finance

Results reported in this research study show that with BF_{10} = 2.35 (<3) and CrI including 0, H3 is not supported, and the direction is uncertain. These results suggest that the aggregate measure of SME credibility is insufficient as an independent factor to reliably influence loan approval outcomes within this sample. The subtle, anecdotal support BF_{10} = 2.35, coupled with the strong theoretical expectation that credibility should matter, suggests credibility might only become an effective signal when complemented by other variables (Aktekin et al., 2018; Ma et al., 2019). This notion of complementarity aligns with the research gap concerning the interplay between traditional credibility markers and emerging digital signals (Mushtaq et al., 2022).

The CRE construct measured competence (business knowledge, skills); expertise (experience in industry); trustworthiness (reliability, integrity); honesty (truthfulness, transparency); accounting records quality and documentation readiness. These emphasise governance quality, reputation, managerial capability and ethical standing. However, lenders prioritise debt-service capacity (cash flows, leverage, margin stability) more. This view is supported by Kinyua et al. (2025), who explicitly report that although accounting records in the form of external audit certification are said to enhance a firm's credibility and the reliability of its financial statements, as well as reduce information asymmetry and increase access to financing, the empirical evidence for this relationship remains inconclusive. In the study for SMEs in the hospitality sector, by Motta and Sharma (2020) it reports that although financial statement lending (proxied by audited financial statements) was expected to increase the likelihood of access to finance, the relationship was only partially supported and significant only in the base model, suggesting that audited statements may not always lead to increased access to finance for this sector. In terms of competence and expertise, it is reported that manager experience has no influence on the probability of having no obstacle to accessing finance, regardless of whether they have external audits (Kinyua et al., 2025).

Contrary to these views Nguyen & Canh (2021) reported that in developing countries, where effective market institutions and business data are absent, banks often rely on trust when lending to private businesses. Furthermore, SMEs joining local industry associations may signal a business's legitimised position in its local market, thus reducing lenders' concerns about information asymmetries.

6.5 H4: The Adoption of AI-Enabled Digital Tools Moderates the Relationship Between SME Credibility and Access to Finance

The results of this study partially supported the adoption of AI-enabled digital tools as the moderator for the relationship between SME credibility and access to finance. The model demonstrated moderate evidence against the null (BF_{10} = 3.94), indicating that the data were approximately four times more consistent with the model incorporating the interaction than with a baseline model assuming no predictors. This view is supported by (Guo et al., 2023) who reported that digital transformation has relatively immediate effects on financing constraints, suggesting recent technology adoption, such as AI, can quickly signal quality without requiring long timeframes. Bao and Huang (2021) share a similar view, reporting that technology-based signals can rapidly influence lending decisions during crises, suggesting that temporal alignment is not always necessary for technology signals to affect credit access. On the contrary, there are several reasons for the partial support found in this study (Li et al., 2024; Nguyen & Canh, 2021). First, lenders could be adopting a parallel assessment approach, whereby technology adoption and credibility are evaluated independently and not assuming that the combination of these two factors could significantly improve the overall assessment (Nguyen & Canh, 2021).

As Belhadi et al. (2025) suggest, specific interactions seem to play a substantial role in explaining the association of digital signals and credibility. Adding that these interactions vary across industries, with digitally driven sectors, such as ICT, software, FinTech and e-commerce showing a stronger and more positive impact. In these environments, AI adoption together with credibility sends a powerful signal to lenders, who expect digital sophistication.

On the contrary, for traditional sectors such as construction, manufacturing and retail, execution makes companies credible over technological capabilities, and there is less dependence on AI in core products and service offerings. Considering the variety of sector composition in the sample, as well as the lack of a dominant sector, strong effects in some sectors and weak or negligible effects in others are potentially responsible for the overall imprecision of the average interaction effect (Li et al., 2024).

In their study, Gama et al. (2024) support the notion that digital tools and AI broadly improve the assessment of SME creditworthiness by mitigating information asymmetry. Similarly, ICT adoption is viewed by banks as an indication of firms' willingness to innovate and creditworthiness, leading to better access to finance (Mushtaq et al., 2022).

6.6 Theoretical Interpretative Framework

6.6.1 **Signalling Theory Perspective**

6.6.1.1 The Evolving Nature of Credible Signals In the Digital Era

Signalling theory assumptions, signals such as traditional signals (collateral, audited financial statements, credit history) should be (1) costly to produce, (2) observable by receivers, and (3) reliably correlated with underlying quality (Spence, 2002). AI-enabled tool adoption and digital footprints are emerging alternative signals. As the results show in the study, they are acknowledged (model evidence) but not acted upon decisively (parameter imprecision). This partial support pattern suggests that these signals may be observable but not yet costly enough or reliably correlate with repayment capacity in the lender's eyes (Colombo, 2021). Digital signals may fail the cost criterion as websites may be purchased cheaply, social presence outsourced, and low-quality firms can fake digital sophistication; therefore, making it difficult to separate high-quality from low-quality firms (Jeza & Lekhanya, 2022).

As Menzies et al. (2025) suggest, credit officers may lack training to interpret digital signals because traditional banks' credit scoring models, built on conventional metrics (collateral, cash flow, credit history), have not been institutionalised and systematically incorporated digital signals into formal evaluation processes. Furthermore, there is a lag effect in the South African context as signals need time to become institutionalised (Li et al., 2024). Therefore, such risk-averse institutions stick with proven signals (Motta & Sharma, 2020). This is a contrast to developed markets, where most signalling research is conducted and FinTech lenders systematically use alternative data, and where AI adoption can reliably predict repayment capacity (Guo et al., 2023; Mushtaq et al., 2022).

6.6.1.2 SME Credibility and Signalling Theory

The empirical analysis for H3, suggesting that SMEs' high credibility (CRE) is more likely to access finance, yielded a verdict of not supported based on the predefined decision rules. Although the model containing only SME Credibility showed anecdotal to moderate evidence in its favour (BF_{10} = 2.35), this result was below the threshold required for robust confidence (BF < 3). In addition, the lack of precision in the estimated effect, indicated by the 95% credible interval (CrI) including zero, prevented definitive conclusions. These results align with Baloyi and Khanyile (2022), who reported that South African SMEs lack conventional credibility signals due to high discontinuity rates, limited supportive regulatory frameworks and economic inequality legacy.

The lack of support for H3, when tested in isolation, appears to contradict the foundational principles of signalling theory, which provides a framework for understanding how SMEs convey their underlying quality to external stakeholders (Colombo, 2021). The result suggests that, for this sample, the aggregate score of SME credibility was insufficient as an independent factor to reliably influence loan approval outcomes.

The failure of CRE to achieve statistical support independently suggests that these conventional factors may not provide a strong enough, unambiguous signal of their own, and that lenders still fundamentally favour the traditional key determinants such as creditworthiness, favourable current ratios, and sustainable profit growth (Belhadi et al., 2025).

The subtle, anecdotal support found for H3 (BF_{10} = 2.35), coupled with the strong theoretical expectation that credibility should matter (Aktekin et al., 2018; Ma et al., 2019), suggests that credibility might only become an effective signal when complemented by other variables. This notion of complementarity aligns with the research gap concerning the interplay between traditional credibility markers and emerging digital signals (Mushtaq et al., 2022), an interaction that was subsequently tested and partially supported under Hypothesis H4. Therefore, the result for H3 alone implies that being credible is necessary but insufficient unless combined strategically with other resources or signals.

6.6.1.3 Digital Footprint and Signalling Theory

The results for H2, stating that SMEs with stronger digital footprints (DFP) are more likely to access finance, yielded a definitive result of not supported. This result contradicts leading literature, grounded in signalling theory (Colombo, 2021; Spence, 2002), which posits that AI and Machine Learning (ML) utilise digital footprints to derive an objective, multi-dimensional enterprise profile, thereby substantially reducing adverse selection costs for capital suppliers (Guo et al., 2024; Li et al., 2023).

From an African contextual barriers perspective, the non-significant results reinforce the nuanced challenges facing SMEs in emerging markets, particularly South Africa. While innovative financing options like mobile lending utilise digital footprints to provide collateral-free loans (Mhlanga, 2021), the overall failure of DFP to predict access might be rooted in fundamental contextual limitations documented in the literature. Specifically, many South African SMEs have not yet fully assimilated digital technology, potentially compromising their ability to generate effective or extensive digital signals that lenders can use and trust (Jeza & Lekhanya, 2022).

6.6.2 **Interpretation of Results Through Information Asymmetry Theory**

6.6.2.1 Persistence of Information Asymmetry Despite AI-Enabled Digital Tools

The results suggest that information asymmetry remains a constraint, evidenced by the 55% rejection rate whereby lenders decline viable firms due to uncertainty. The lack of decisive support for digital signals (H2, H3) suggests that more information does not automatically reduce asymmetry (Calabrese et al., 2021; Guo et al., 2023). Critical insight drawn from the results is that although digital tools generate more data, they may not necessarily provide more decision-relevant data. This is contrary to Guo et al. (2024), who suggest that digital transformation significantly alleviates financing barriers and Li et al. (2023) supply-side view that AI enables multi-dimensional credit evaluation and increases transparency. This perspective is also shared by Mhlanga (2021), who states that AI-based apps overcome information asymmetry through alternative data. This contradictory view is due to studies often focusing on FinTech lenders and not traditional banks, consumer lending and not SME lending, and developed markets (not the South African context).

6.6.2.2 Credit Rationing and Adverse Selection: Unresolved Issues in an Information Asymmetry Environment

In this study, small enterprises with 11–50 employees reported 100% loan approval, while very small enterprises consisting of 5–10 employees a 23.8% reported loan approval. These results suggest size-based credit rationing as loan approval increasingly relies on firm size rather than quality (Ma et al., 2019). From an adverse selection perspective, although the digital transformation promise suggests the use of alternative data, such as digital footprints of a firm, should separate high-quality firms from low-quality firms (Jagtiani & Lemieux, 2019; Li et al., 2024), it is inconsistent with the study's results that digital footprints do not effectively separate quality or decisively distinguish firms. Contrary to Mhlanga (2021), where mobile data is reported to be successfully used for credit scoring in developing countries such as Kenya, Nigeria, India and Mexico, albeit in a FinTech context. This suggests that digital signals do not yet solve adverse selection and that while digital tools provide more data, it has not eliminated screening challenges (Motta & Sharma, 2020).

6.7 Insights From Control Variables

Insights drawn from control variables suggest that traditional credit factors demonstrate clearer, more decisive patterns in loan approval likelihood compared to emerging digital signals (AIA, DFP, CRE), reinforcing the conclusion that these established metrics remain primary filters in credit assessment (Belhadi et al., 2025).

First, the study showed that the level of education, such as Bachelor's/Postgraduate qualifications, showed a higher loan approval rate. This is in line with the human capital metrics, such as the entrepreneur's educational background, which serve as vital signals of competence and managerial capability to lenders (Colombo, 2021). The characteristics of the entrepreneur, rather than the firm itself, are important for determining the impact of increased access to credit for small firms (Bryan et al., 2024).

Second, from the study, firms operating over ten years showed a higher loan approval (66.7%) compared to firms operating 3–5 years (22.6%), suggesting that firm maturity significantly influences lender decisions, acting as a crucial signal of stability. Older firms establish a robust track record of financial performance (Rao et al., 2023), which mitigates uncertainty for lenders (Kinyua et al., 2025). New firms are characterised by greater opaqueness and typically have less collateral available, making them more likely to be denied loans or have their loan amounts scaled back (Calabrese et al., 2021). Older firms, in contrast, are more likely to gain access to finance (Nguyen & Canh, 2021) because they demonstrate a proven business model and survival ability (Quartey et al., 2017).

Third, firm size (measured by employees or assets) remains a powerful determinant. The study showed that medium-sized firms with 11–50 employees reported 100% approval, demonstrating that size and stability matter acutely to lenders. Smaller firms are consistently found to face greater obstacles to accessing finance compared to large enterprises (Mushtaq et al., 2022). This size-based rationing persists despite efforts toward digital transformation; for example, micro firms are 2.76 times more likely to be discouraged from seeking credit than medium-sized firms (Anastasiou et al., 2025). Banks prefer to approve loans from large enterprises due to their asset size and proven track record, even when small firms provide adequate collateral (Ma et al., 2019). Indeed, the number of employees is shown to increase the probability of a firm reporting no obstacles to finance (Kinyua et al., 2025)

This pattern confirms that business financial health indicators, such as the current ratio, leverage, and profit margins, remain central to creditworthiness (Belhadi et al., 2025). Core financial metrics like profit growth are essential indicators of competence and are often the factor that most affects borrowing capacity and the likelihood of loan repayment in conservative credit environments (Nguyen & Canh, 2021).

6.8 Conclusion

In this chapter, the quantitative results from Chapter 5 were discussed, focusing on the influence of AI-enabled tool adoption (AIA), digital footprints (DFP), and SME credibility (CRE) on loan approval outcomes for South African SMEs, analysed through signalling theory and information asymmetry theory.

The theoretical insights contribute to signalling theory, which highlights that digital signals function as emerging credibility markers in the South African traditional banking context, requiring sufficient costs to prevent imitation and alignment with lender priorities. The study suggests that the effectiveness of these signals is context-contingent, and temporal dynamics indicate that signals needed time to become institutionalised.

Contributions to information asymmetry theory revealed a hierarchy of information types, with private financial data being more significant than public digital presence for SME lending. Persistent problems such as credit rationing, adverse selection, and moral hazard were identified, emphasising that the quality and relevance of information mattered more than the quantity.

The chapter also highlighted unique challenges faced by emerging markets, such as lender conservatism and a high rejection rate of 55%, indicating persistent constraints despite technological advances.

The major conclusion was that while the adoption of technology and credibility are relevant signals in the financial inclusion, traditional credit mechanics remain the primary filters for lenders in South Africa's SME financing context. Digital signals were acknowledged but not yet decisive, context-dependent and in a transitional phase toward institutionalisation. This nuanced understanding reconciled contradictory results, indicating that while digital transformation is important for SME competitiveness, traditional financial metrics continue to drive lending decisions. As digital adoption matures, the influence of digital signals may strengthen, but fundamentally, loan approval decisions rely on the demonstrable capacity to generate cash flows and repay debt.

The results and theoretical insights presented in this chapter provide the foundation for Chapter 7, which will synthesise the overall conclusions about AIA, DFP and CRE signals in SME financing. It will provide evidence-based recommendations for multiple stakeholders and outline directions for future research addressing identified limitations. Broader implications for SME development policy and financial inclusion in South Africa will also be discussed.

Chapter 7: Conclusions and Recommendations

7.1 Introduction

The vast majority of prior research clearly established information asymmetry as the primary systemic obstacle to accessing funding by small and medium enterprises (SMEs) in both global and developing markets (Guo et al., 2023; Rao et al., 2023). However, there had been very limited empirical evidence concerning the effectiveness of emerging, digitally driven solutions that remained largely untested in the local context. Thus, the major unknown was whether data generated through digitally based signals, such as AI-enabled tool usage and digital footprints, would affect the decisions made by financial institutions in the South African environment.

International studies have demonstrated that firms using FinTech platforms to leverage such data were successful in doing so (Jagtiani & Lemieux, 2019; Li et al., 2024; Mhlanga, 2021); however, there has been an overwhelming lack of research conducted in Africa, which made it impossible to generalise results to the conservative local banking industry (Hassan, 2024; Rao et al., 2023). In addition, the substantial imbalance of academic attention toward the supply-side (i.e. lenders adopting and utilising technology) relative to the demand-side (SMEs' digital transformation) created another gap in the literature. As a result, the study adopted a demand-side perspective (Guo et al., 2023; Jeza & Lekhanya, 2022).

It was unclear how SME credibility (CRE), as defined by traditional characteristics, interacted with emerging digital signals (Colombo, 2021). Therefore, the study sought to determine the degree to which digital signals substituted or complemented traditional creditworthiness indicators, such as audited statements and tangible collateral (Motta & Sharma, 2020; Mushtaq et al., 2022). Understanding this interaction was important from a context-specific perspective and how effective digital transformation is as a strategic approach for local SMEs attempting to overcome financial exclusion (Baloyi & Khanyile, 2022). It was from these unknowns that the primary research objectives and hypotheses were developed.

From a methodological point of view, a quantitative cross-sectional design was adopted, and the hypotheses testing the relationship between AIA, DFP, CRE and loan approval were conducted utilising the Bayesian logistic regression. This analytical approach is appropriate for the limited sample size as it employs weakly informative priors to stabilise estimation and uses Bayes Factors (BF_{10}) and credible intervals (CrI) to offer a balanced interpretation of support beyond traditional binary significance thresholds (Aktekin et al., 2018).

7.2 Summary of the Key Results and Theoretical Contributions

Table 7.1: Summary of Hypotheses Testing Results

Hypothesis	$\mathbf{BF_{10}}$	**Decision**
H1: AI Adoption	12.20	Partial support
H2: Digital Footprint	0.36	Not supported
H3: SME Credibility	2.35	Not supported
H4: Interaction Effect – AIA & CRE	3.94	Partial support

Source: Researcher's compilation (2025)

7.2.1 **Context-Specific Signalling Efficacy**

The results suggest that there is a fundamental role of context in the effectiveness of any signal. Digital signals (AI adoption, digital footprints) showed model-level recognition (BF_{10} = 12.20 for AIA) but not parameter-level decisiveness, uncovering a recognition-action gap where lenders recognise certain signals as important but do not possess the institutional perspective to act conclusively on them (Li et al., 2024). This is to introduce the concept of transitional signals, indicators that are partially institutionalised: noticed but not systematically followed in script selection. This is the opposite of developed markets, where digital signals exhibit recognition and leading influence.

7.2.2 **The Principle of Signal Complementarity**

The results indicate that traditional credibility signals are necessary but not sufficient alone (BF_{10} = 2.35), but they are augmented when combined with AI adoption (BF_{10} = 3.94). This shows that signals are a collection rather than an independent indicator in the presence of persistent asymmetry.

7.2.3 **Information Quality Over Quantity**

A central result is that information type being signalled matters more than the quantity; whilst digital transformation generates abundant data points through AI tools and digital footprints (Guo et al., 2023; Huang et al., 2025), the 55% loan application rejection rate demonstrates that this volume does not automatically reduce asymmetry unless the information is explicitly decision-relevant and reduces uncertainly regarding an SMEs repayment capacity (Li et al., 2024; Luo et al., 2024).

7.2.4 **Persistent Credit Rationing and Adverse Selection**

Nontraditional data sources have failed to eliminate the inherent problems associated with traditional credit rationing and adverse selection (Ma et al., 2019). In the study, medium sized enterprises achieved 100% approval and small enterprises with 5–10 employees were approved at a rate of 23.8%, thus supporting the view that traditional size-based rationing is an ongoing approach (Anastasiou et al., 2025; Mushtaq et al., 2022), which is consistent with previous concerns about the failure of competitive markets when there is imperfect information.

7.2.5 **Context-Specificity in Emerging Markets**

This result provides strong support for the idea of context specificity, suggesting that assumptions or successes found in developed FinTech markets (Jagtiani & Lemieux, 2019; Mhlanga, 2021) cannot simply be extended to traditional South African institutions that face severe financing constraints (Baloyi & Khanyile, 2022; Jeza & Lekhanya, 2022; Rao et al., 2023). Thus, it supports the notion that verifiable quality data over quantity will continue to govern the utility of information in this high asymmetry setting (Calabrese et al., 2021; Motta & Sharma, 2020).

7.2.6 **Bridging Theory and Context**

The study bridges theoretical expectations and practical realities by providing a means of reconciling contradictory evidence regarding digital signalling from a critical contextual perspective. The study suggests that the South African lending environment is currently in a transitional phase during which digital signals (AIA and DFP) are recognised as new indicators of innovation but have not been incorporated into traditional banking assessment frameworks (Jagtiani & Lemieux, 2019; Mushtaq et al., 2022). This indicates that traditional lending practices, particularly hard financial data, such as positive cash flows, collateral and track record, remain the primary factors used to assess loan applications and consistently supersede the use of nontraditional cues (Motta & Sharma, 2020). As Jeza and Lekhanya (2022) posits, digital footprint and sophistication is thus shown to be necessary for SME competitiveness and operational efficiency, but fundamentally insufficient for credit approval when lacking decisive correlation with underlying financial capacity.

7.3 Practical Implications

7.3.1 **Implications for SMEs**

The success of formal loan applications for South African SMEs is dependent on attaining financial credibility that can be verified, along with clear signals to lenders (Baloyi & Khanyile, 2022; Rao et al., 2023). In this regard, SMEs should give preference to financial basics; they should concentrate heavily on basic financial health position, as hard metrics such as the stability of cash flow and sustainable profit growth are more significant than projected sales figures (Motta & Sharma, 2020). It is essential for SMEs to maintain accurate and timely accounting records and be prepared with proper documentation, as a lack of reliable financial statements severely exacerbates information asymmetry, thus stifling access to finance (Guo et al., 2023; Rao et al., 2023). To establish a good financial track record, SMEs should aim at showing stable performance over time, with positive current ratios and reducing the dependence on long-term debt for operational purposes (Belhadi et al., 2025; Le et al., 2024).

Entrepreneurs should take a strategic digital adoption approach of going beyond only being visible online to embedding AI-enabled tools within the core of their operations to generate identifiable efficiency gains and build risk resilience (Guo et al., 2023). Significantly, such digital interventions need to be well-implemented and sustained in order to prevent operational challenges that may undermine their signal value (Jeza & Lekhanya, 2022). In addition, sufficient time must be allowed for the efficiency benefits to materialise as visible improvements in financial statements before seeing formal credit (Gama et al., 2024). To enhance their standing, SMEs must establish credibility through various means by carefully integrating traditional sources of credibility markers such as expertise, trustworthiness, and transparency with digital acumen (Forstner et al., 2025; Motta & Sharma, 2020). Formal networks such as industry associations and professional networks can provide legitimacy, facilitate information sharing, and help mitigate the information asymmetry in the credit market (Quartey et al., 2017; Zhang et al., 2025).

Lastly, digital strategies should be contextually linked, because while a strong public online presence may be vital for e-commerce, B2B sectors should focus on strengthening long-term creditworthy supply chain relationships, which can improve financing terms through proprietary information sharing (Belhadi et al., 2025; Jeza & Lekhanya, 2022).

7.3.2 Implications for Lenders

Financial institutions operating in the South African market are urged to prioritise the gradual integration of digital signals, utilising them primarily in a complementary context rather than an outright replacement of fundamental financial assessment models (Motta & Sharma, 2020). Critically, banks need to develop tailored lending products for smaller enterprises to directly address persistent size-based credit rationing (Anastasiou et al., 2025). Digital sophistication could be considered a mitigating factor for size-related risks (Yang et al., 2024), thereby balancing stringent risk management with crucial financial inclusion objectives (Mhlanga, 2021). This necessary transition requires dedicated investment in credit officer training to interpret complex digital signals effectively, as specialised skills are necessary to move beyond simplistic data aggregation (Menzies et al., 2025; Mushtaq et al., 2022; Li et al., 2024). Finally, acknowledging that signals require time to become institutionalised, lenders should anticipate lag effects in the financial benefits accruing from SME AI adoption (Gama et al., 2024).

7.3.3 Implications for Policymakers

Policymakers need to strengthen their efforts and put in place targeted interventions that alleviate structural financial constraints for South African SMEs to create employment and grow the economy (Baloyi & Khanyile, 2022; Rao et al., 2023). Mutual support around digital infrastructure and capability building is needed in the form of funded training and digital literacy programmes to ensure that SMEs cross the digital divide and maintain their upskilling levels, considering the fast-changing technology (Hassan, 2024; Jeza & Lekhanya, 2022; Mushtaq et al., 2022).

In addition, policymakers should actively enhance the information-sharing structure, encouraging open banking mechanisms that will make it possible to safely exchange financial information and reduce market information asymmetry (Quartey et al., 2017; Rao et al., 2023). Establishing and enabling a regulatory environment is essential, and there is a need to provide clear regulatory norms for the fair use of alternative credit data and to encourage lenders through incentives to use innovative risk-management evaluation approaches (Hassan, 2024; Li et al., 2024). Lastly, the support of government, such as credit guarantee measures, also play a crucial role in signalling firm quality, creating internal capacity and enhancing access to market-based finance (Arroyabe et al., 2024; Quartey et al., 2017).

7.4 Limitations of the Study

7.4.1 Sample and Time-Horizon Limitations

The study surveyed 180 respondents, which is a sample size that is broadly respectable and exceeds the common benchmark for logistic regression analysis. However, the challenge is that only 89 respondents from this sample had applied for a loan, which resulted in a relatively small final sample (n = 89). This size imposed practical limitations on the degree of statistical power attained, limiting the depth of inference and preventing robust subsample analyses by business sector, despite evidence that SME financial behaviour and signalling requirements differ significantly across industries (Arroyabe et al., 2024; Rao et al., 2023).

Furthermore, the cross-sectional nature of the study limited data collection to a single point in time. Therefore, the conclusion of the study can only indicate an association between variables, rather than definitively establishing causality or understanding how AI adoption and digital footprints change over time to influence lending decisions (Calabrese et al., 2021; Hassan, 2024; Motta & Sharma, 2020).

Finally, relying on self-reported information from SME owners and co-owners exposes the results to potential biases, including social desirability and recall biases that may have influenced data quality (Podsakoff et al., 2003). However, the nature of the concepts under study is that they are subjective and therefore can be captured with self-reports, similar to other scholars (Saunders & Lewis, 2018).

7.4.2 **Measurement Limitations**

Some measurement options provide limitations on the precision of the constructs. The AI adoption measure primarily captured the extent of tool adoption (which AI-enabled digital tools were used), but not necessarily the depth or success of integration and use for core operations. This limits insight into whether adoption was merely superficial or genuinely embedded in the firm. Similarly, the digital footprint (DFP) construct was operationalised as a composite measure that aggregated metrics across different digital platforms. This pooling, therefore, may have masked platform-specific effects and heterogeneity (Li et al., 2024), which could be in part responsible for why the construct emerges as a poor predictor. The SME credibility (CRE) construct largely stressed governance and reputation signals, rather than focusing holistically on direct evidence of financial capability. Finally, being only able to see a binary loan approval decision (yes or no) may have led to the exclusion of some important nuances, such as the specific approval amounts, the terms negotiated, or instances of partial loan approvals.

7.4.3 **Methodological Limitations**

The methodological framework, while robust for the sample size, carries intrinsic constraints. Although the Bayesian approach was employed to stabilise estimation amidst the modest sample, the results remain somewhat dependent on the prior specification choices made. The primary analytical tool, binary logistic regression, cannot fully control for unobserved heterogeneity, unmeasured firm-specific factors related to intrinsic SME quality, which may subsequently bias estimates concerning financial performance (Calabrese et al., 2021). Due to the cross-sectional nature, the analysis possesses a limited ability to assess causality, and the exploration of complex non-linear relationships, such as interaction effects, often requires greater statistical power than was available in the sample to achieve decisive precision. Endogeneity, where the loan outcome might influence subsequent signalling decisions (reverse causality), is a persistent concern that cannot be eliminated in this type of design (Guo et al., 2023).

7.5 Recommendations for Future Research

The limitations observed in this quantitative study highlight several key areas, which future research may consider when seeking to deepen the understanding of the signalling influence of AI-enabled technologies, digital footprints and SME credibility within the challenging context of South African SME financing or similar emerging markets. Therefore, given the relatively small effective sample, we plan to replicate this study with a larger sample to determine whether the observed results persist.

First, longitudinal research may be conducted to go beyond cross-sectional relationships, enabling researchers to track SMEs over time in order to examine causality (Wei et al., 2025) as well as to evaluate lasting effects on venture sustainability (Luo et al., 2024). In addition, measure the inevitable lag effects that accrue before technological benefits are translated into financial performance measures (Guo et al., 2023; Luo et al., 2024).

Secondly, the mixed-method approach (quantitative and qualitative) whereby interviews with lenders are included is vital (Colombo, 2021). This may help unpack the complex cognitive decision-making processes used by traditional credit officers when interpreting nontraditional digital signals (Bryan et al., 2024). Critically, larger samples are required for future research for robust, sector context-specific testing to be conducted, especially as there is a high degree of heterogeneity regarding SMEs from different sectors (Belhadi et al., 2025; Guo et al., 2023).

Furthermore, future research should develop more nuanced measurement instruments for construct refinement. The definition of AI adoption should be updated to measure the depth and quality of utilisation and integration rather than simply illustrating presence (Guo et al., 2023; Huang et al., 2025). To address the noise associated with aggregation, signals in digital footprints should be studied on a platform-specific basis, instead of relying on composite scores, like how some advanced lending systems' capabilities of analysing specific sources individually to make better decisions (Li et al., 2024).

Researchers may also consider developing refined dimensions of credibility and making a clear distinction between soft elements, such as governance or reputation, and hard objective indicators regarding a firm's financial standing. Finally, research results must be made more nuanced and go beyond binary approval status to examine critical variables such as loan amounts, interest rates, as well as terms and conditions of credit to effectively evaluate the credit allocation efficiency and potential misallocations (Bryan et al., 2024; Motta & Sharma, 2020).

7.6 Study Conclusion

This study examined the influence of AI-enabled digital tool adoption, digital footprint and credibility on loan approval outcomes for South African SMEs. Primary data was collected through a survey from owners and co-owners of SMEs and analysed through Bayesian logistic regression to assess the relationship between the respective constructs.

The findings reveal a nuanced landscape where digital signals exhibit recognition-level importance but lack decisive influence in traditional lending decisions, therefore introducing the concept of transitional signals within South Africa's conservative banking environment. While the relevance of AI adoption did display some evidence (BF_{10} = 12.20) and more so when combined with traditional credibility markers (BF_{10} = 3.94), neither digital footprints nor credibility by themselves evidenced robust support to clearly influence loan outcomes. The 55% decline rate and continued size-based rationing suggest that while digital transformation has operational advantages for SMEs, it remains insufficient to overcome entrenched information asymmetries without accompanying verifiable financial capacity.

The theoretical contribution made by this research study is by highlighting the context-dependent nature of signalling efficacy, questioning the generalisation of insights across more developed FinTech markets to emerging markets. From a practical perspective, the research highlights that South African SMEs need to continue focusing on strong financial fundamentals and combine them with strategic adoption of digital technologies. Furthermore, lenders require institutional adjustment to understand nontraditional signals that could assist in making real-life lending decisions. Ultimately, bridging the recognition gap requires joint efforts between SMEs, financial institutions, and policymakers to assist in the facilitation of the gradual institutionalisation of digital signals within South Africa's evolving credit assessment landscape.

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List of Appendices

Appendix A: Invitation to Participate & Informed Consent Statement

Section 1 of 7

The Impact of AI-Enabled Tools, Digital Footprints, and SME Credibility on Loan Approval Decisions: A Quantitative Study of South African Small and Medium Enterprises

Dear Respondent,

I am currently a student at the University of Pretoria's Gordon Institute of Business Science (GIBS), where I am completing my research in partial fulfilment of a Master's in Business Administration. I am conducting a research study to investigate the impact of AI-enabled digital tools, SME credibility, and digital footprints on loan approval outcomes for South African Small and Medium Enterprises (SMEs), with the aim of deepening understanding of digital transformation as a driver of financial inclusion.

You have been identified as a potential respondent to the questionnaire of this study, and I believe your response will be invaluable.

The questionnaire should take no longer than 10 minutes of your time. Please note your participation is anonymous and that all records collected during this study will be treated with confidentiality. Results will be presented in a manner that ensures respondents' identities remain unidentified.

Your participation is voluntary, and you have the freedom to withdraw at any time without penalty. By completing this survey, you indicate your voluntary participation in this research.

The questionnaire will be collected electronically through Google Forms. Your responses will be saved in Google Drive, a cloud-based platform that offers encryption capabilities and password protection.

Should you have any queries, please do not hesitate to contact me. I have also included my supervisor's details below, with your consent.

Thank you in advance for all your assistance in this regard.

Researcher name: [redacted]
Email: [redacted]

Researcher supervisor: [redacted]

Appendix B: Instrument (Survey)

Section 1: Business Profile

Qualifying question

*** What is your role in the business? [Select one]**

- ☐ Owner
- ☐ Co-owner
- ☐ Key decision maker (e.g. Finance Manager, Sales Manager, Operations Manager, HR Manager, Investor)
- ☐ None of the above [Thank you message terminating the survey]

1. **Age:** Which of the following age brackets applies to you?
    1. 18 – 24 years old
    2. 25 – 34 years old
    3. 35 – 44 years old
    4. 45 – 54 years old
    5. 55+ years old
2. **Gender:** Which of the following is your gender?
    1. Female
    2. Male
    3. Non-binary
    4. Prefer not to say
3. **Education:** What is the highest grade or level of education you have successfully completed?
    1. Grade 8–9 (Incomplete Secondary)
    2. Grade 10–11 (Incomplete Matric)
    3. Grade 12 / Matric (NQF Level 4)
    4. Certificate (NQF Level 5, e.g., TVET)
    5. Diploma (NQF Level 6)
    6. Bachelor's Degree (NQF Level 7)

7. Honours / Postgrad Diploma (NQF Level 8)
8. Master's or PhD (NQF Level 9–10)

4. * **Years of operation:** How many years has your business been operating?
    1. Less than 1 year
    2. 1 – 2 years
    3. 3 – 5 years
    4. 6 – 10 years
    5. More than 10 years

5. * **Number of employees:** How many full-time employees (including owner) does your business currently have?
    1. 0 (Only owner)
    2. 1 – 4 (Micro-enterprise)
    3. 5 – 10 (Small enterprise)
    4. 11-50 (Medium enterprise)
    5. 51+ (Outside SMME definition)

6. * **Business sector:** In which sector does your business primarily operate? (Select from the list)

    - ☐ Agriculture, Forestry & Fishing
    - ☐ Mining & Quarrying
    - ☐ Manufacturing
    - ☐ Electricity, Gas & Water Supply
    - ☐ Construction
    - ☐ Wholesale & Retail Trade; Repair of Motor Vehicles, Motorcycles & Personal Goods
    - ☐ Accommodation & Food Services
    - ☐ Transport, Storage & Communication
    - ☐ Financial & Insurance Services
    - ☐ Real Estate & Business Services
    - ☐ Community, Social & Personal Services

- Education & Training
- Health & Social Work
- Arts, Entertainment & Recreation
- Information & Communication Technology (ICT)
- Professional, Scientific & Technical Services
- Administrative & Support Services
- Public Administration & Defence
- Environmental & Green Economy Services
- Other (Please specify)

7. **Province:** In which province is your business located? (Select from the list)
   - Eastern Cape
   - Free State
   - Gauteng
   - KwaZulu-Natal
   - Limpopo
   - Mpumalanga
   - Northern Cape
   - North West
   - Western Cape
8. **Financial decision maker:** Who manages financial decisions in your business? (Select from the list)
   - Business owner
   - Finance manager
   - Business partner
   - Other (please specify)
9. **Financial Knowledge:** On a scale of 1 to 7, where one means very low and seven means very high, how would you assess your overall financial knowledge?
   1. 1

2. 2
3. 3
4. 4
5. 5
6. 6
7. 7

Section 2: AI-Enabled Digital Tool Adoption

10. **Enterprise software usage:** Our business uses enterprise software (e.g., accounting software – QuickBooks, Sage, Xero).

 1 = Never

 2 = Rarely

 3 = Sometimes

 4 = Often

 5 = Always

11. **Online order processing:** We receive and process orders, inquiries, or comments through our website or other online channels.

 1 = Never

 2 = Rarely

 3 = Sometimes

 4 = Often

 5 = Always

12. **Information sharing across the supply chain:** Information systems enable us to share inventory and operational information with suppliers or partners, and these processes are carried out electronically.

 1 = Strongly Disagree

 2 = Disagree

 3 = Neutral (or Neither Agree nor Disagree)

 4 = Agree

 5 = Strongly Agree

13. **Strategic necessity of digital tools**: We believe it is strategically necessary to use digital technologies in our business. For example, an E-commerce platform (Shopify), data analytics tools (Power BI), and automation tools (Zapier)

    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree

14. **Performance metric:** We have clearly defined parameters for measuring the performance of our AI-enabled digital tools, such as our website or social media accounts.

    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree

15. **Digital planning and resources:** Our business has a digital plan with clearly defined activities, responsible people, and budgets, and people with digital-marketing knowledge are responsible for implementation.

    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree

Section 3: SME Credibility

16. **Experience:** Our business keeps accurate and up-to-date financial records.

    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree

17. **Competence:** Our business is skilled at what we do.

- 1 = Strongly Disagree
- 2 = Disagree
- 3 = Neutral (or Neither Agree nor Disagree)
- 4 = Agree
- 5 = Strongly Agree

18. **Expertise:** Our business has a high level of expertise in its line of work

- 1 = Strongly Disagree
- 2 = Disagree
- 3 = Neutral (or Neither Agree nor Disagree)
- 4 = Agree
- 5 = Strongly Agree

19. **Trustworthiness:** I trust our business to keep its promises.

- 1 = Strongly Disagree
- 2 = Disagree
- 3 = Neutral (or Neither Agree nor Disagree)
- 4 = Agree
- 5 = Strongly Agree

20. **Honesty of claims:** Our business makes truthful claims and is honest in communications

- 1 = Strongly Disagree
- 2 = Disagree
- 3 = Neutral (or Neither Agree nor Disagree)
- 4 = Agree
- 5 = Strongly Agree

21. **Accurate records:** Our business keeps accurate and up-to-date financial records.

- 1 = Strongly Disagree
- 2 = Disagree

- 3 = Neutral (or Neither Agree nor Disagree)
- 4 = Agree
- 5 = Strongly Agree

22. **Documentation readiness:** We can provide all required documents when applying for funding.
    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree

Section 4: Digital Footprint

23. **Active website:** We have an active business website.
    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree
24. **Social-media activity:** We are active on social media platforms (e.g., Facebook, LinkedIn, Instagram).
    - 1 = Never
    - 2 = Rarely
    - 3 = Sometimes
    - 4 = Often
    - 5 = Always
25. **Interactive website features:** Our website includes visual brochures and interactive search options, and customers can follow publications and promotions.
    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)

- 4 = Agree
- 5 = Strongly Agree

26. **Performance analytics:** We have clearly defined metrics for measuring the performance of our overall online presence, including our website and social media platforms.

    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree

27. **Digital-marketing planning:** Our company has a digital-marketing plan with clearly defined activities, responsible executors and budgets.

    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree

28. **Digital-marketing expertise:** People with knowledge in digital marketing are responsible for implementing our online presence.

    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral (or Neither Agree nor Disagree)
    - 4 = Agree
    - 5 = Strongly Agree

Section 5: Access to Finance (Loan Approval)

29. **Loan application:** Have you applied for a business loan in the past 12 months?

    - Yes
    - No

30. Loan outcome: If yes, was the loan approved?

    1. Yes

2. No

Section 6: Use of AI tools

31. Has your business adopted AI tools or technologies in its operations (E.g. ChatGPT, DeepSeek, Copilot)

    1. Yes

    2. No

32. **Which functions are AI tools used for?**

- Operations
- Finance
- Marketing
- Customer Service
- Sales

Appendix C: Ethics Approval

Ethical Clearance Approved External Inbox ×

Masters Research <MastersResearch@gibs.co.za>

to me, Masters

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear [redacted]

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIB Research Admin team.

Appendix D: SME Classification

Previous SME Classification Criteria by Sector under the National Small Enterprise Act (1996) and 2003 Amendment

Column 1	Column 2	Column 3	Column 4	Column 5
Sector or sub-sectors in accordance with the Standard Industrial Classification	**Size or class**	**Total full-time equivalent of paid employees** **Less than**	**Total annual turnover** **Less than**	**Total gross asset value (fixed property excluded)** **Less than**
Agriculture	Medium	100	R 4.00 m	R 4.00 m
	Small	50	R 2.00 m	R 2.00 m
	Very small	10	R 0.40 m	R 0.40 m
	Micro	5	R 0.15 m	R 0.10 m
Mining and Quarrying	Medium	200	R30.00 m	R18.00 m
	Small	50	R 7.50 m	R 4.50 m
	Very small	20	R 3.00 m	R 1.80 m
	Micro	5	R 0.15 m	R 0.10 m
Manufacturing	Medium	200	R40.00 m	R15.00 m
	Small	50	R10.00 m	R 3.75 m
	Very small	20	R 4.00 m	R 1.50 m
	Micro	5	R 0.15 m	R 0.10 m
Electricity, Gas and Water	Medium	200	R40.00 m	R15.00 m
	Small	50	R10.00 m	R 3.75 m
	Very small	20	R 4.00 m	R 1.50 m
	Micro	5	R 0.15 m	R 0.10 m
Construction	Medium	200	R20.00 m	R 4.00 m
	Small	50	R 5.00 m	R 1.00 m
	Very small	20	R 2.00 m	R 0.40 m
	Micro	5	R 0.15 m	R 0.10 m
Retail and Motor Trade and Repair Services	Medium	100	R30.00 m	R 5.00 m
	Small	50	R15.00 m	R 2.50 m
	Very small	10	R 3.00 m	R 0.50 m
	Micro	5	R 0.15 m	R 0.10 m
Wholesale Trade, Commercial Agents and Allied Services	Medium	100	R50.00 m	R 8.00 m
	Small	50	R25.00 m	R 4.00 m
	Very small	10	R 5.00 m	R 0.50 m
	Micro	5	R 0.15 m	R 0.10 m
Catering, Accommodation and other Trade	Medium	100	R10.00 m	R 2.00 m
	Small	50	R 5.00 m	R 1.00 m
	Very small	10	R 1.00 m	R 0.20 m
	Micro	5	R 0.15 m	R 0.10 m
Transport, Storage and Communications	Medium	100	R20.00 m	R 5.00 m
	Small	50	R10.00 m	R 2.50 m
	Very small	10	R 2.00 m	R 0.50 m
	Micro	5	R 0.15 m	R 0.10 m
Finance and Business Services	Medium	100	R20.00 m	R 4.00 m
	Small	50	R10.00 m	R 2.00 m
	Very small	10	R 2.00 m	R 0.40 m
	Micro	5	R 0.15 m	R 0.10 m
Community, Social and Personal Services	Medium	100	R10.00 m	R 5.00 m
	Small	50	R 5.00 m	R 2.50 m
	Very small	10	R 1.00 m	R 0.50 m
	Micro	5	R 0.15 m	R 0.10 m

Source: *Government of South Africa. National Small Enterprise Act 102 of 1996; National Small Business Amendment Act 26 of 2003. Compiled from the Schedule detailing sector-specific numerical criteria for employees, turnover, and total gross assets.*

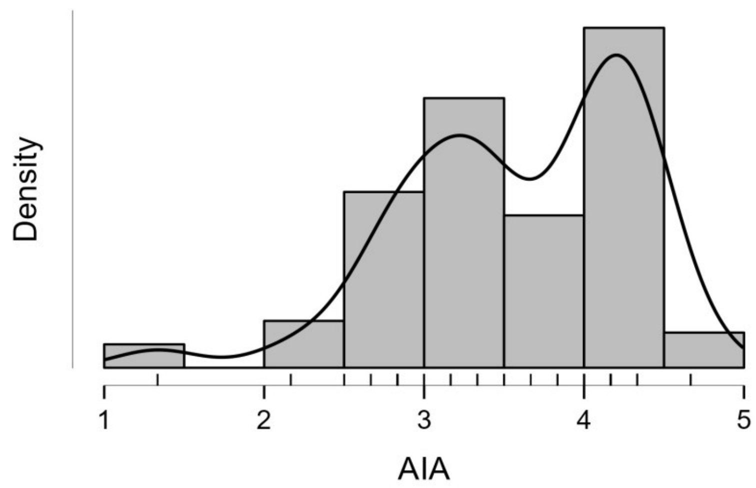
Appendix E: JASP Output_ Analysis_13Oct25

Descriptive Statistics

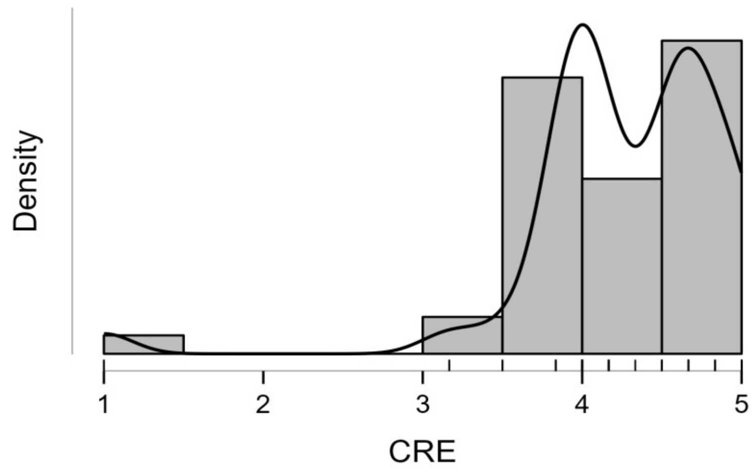
	Valid	Mean	Std. Deviation	Minimum	Maximum
AIA	89	3.597	0.719	1.333	4.667
CRE	89	4.266	0.667	1.000	5.000
DFP	89	3.479	1.011	1.000	5.000

Appendix F: Distribution Plots

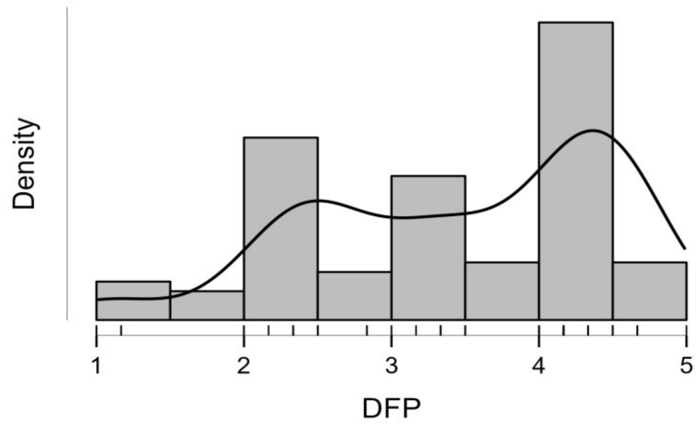
AIA



CRE



DFP



Appendix G: Bayesian Logistic Regression

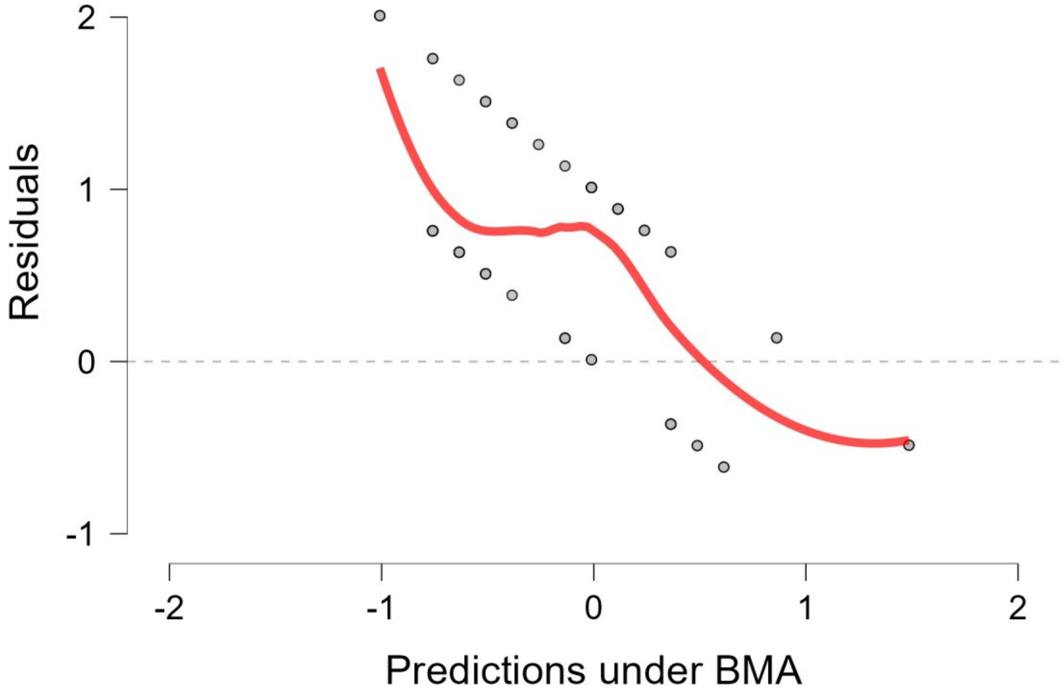
Model Comparison – q33_loan_approved

Models	P(M)	P(M|data)	BF_M	BF_{10}	R^2
Null model	0.500	0.076	0.082	1.000	0.000
AIA	0.500	0.924	12.197	12.197	0.077

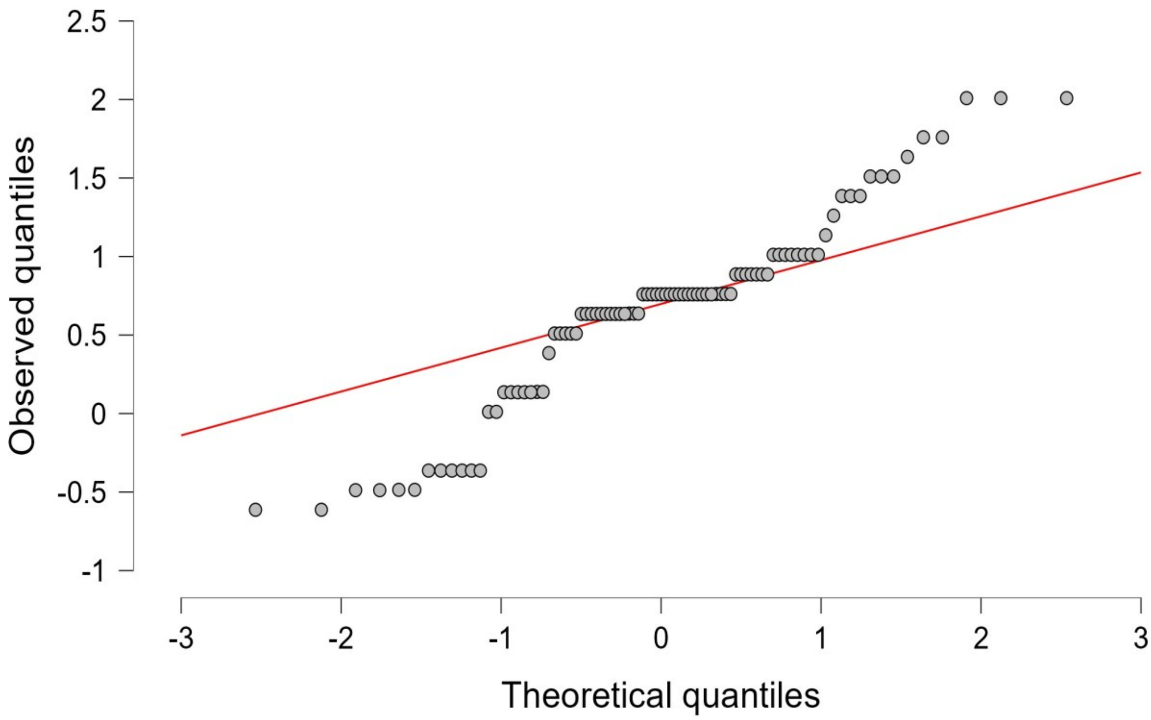
Posterior Summaries of Coefficients

								95% Credible Interval	
Coefficient	P(incl)	P(excl)	P(incl|data)	P(excl|data)	$BF_{inclusion}$	Mean	SD	Lower	Upper
Intercept	1.000	0.000	1.000	0.000	1.000	3.053	1.528	−0.355	5.575
AIA	0.500	0.500	0.924	0.076	12.197	−0.748	0.369	−1.327	0.000

Appendix H: Residuals vs Fitted



Q-Q Plot



DV/Factor Descriptives

DV/Factor	Level	N
q33_loan_approved	0	49
	1	40

Covariate Descriptives

	N	Mean	SD
AIA	89	3.597	0.719

Appendix I: Bayesian Logistic Regression 2

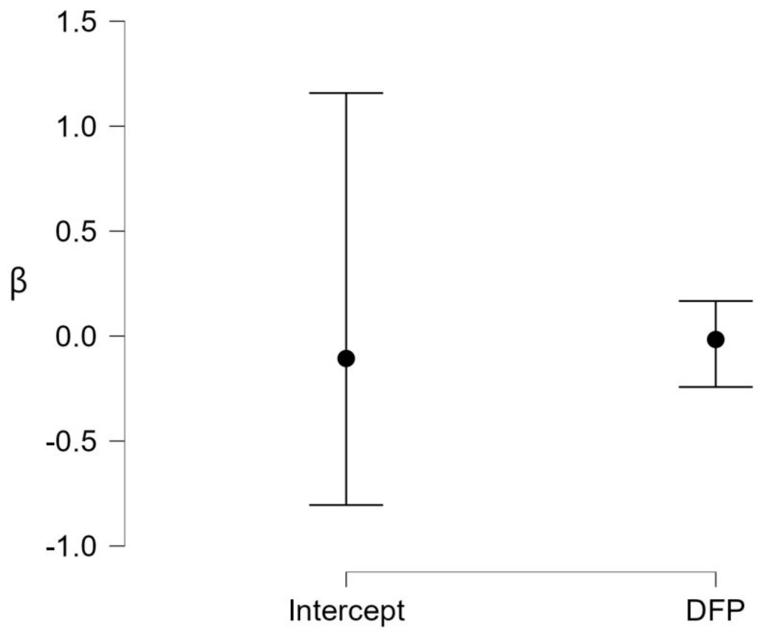
Model Comparison – q33_loan_approved

Models	P(M)	P(M|data)	BF_M	BF_{10}	R^2
Null model	0.500	0.736	2.790	1.000	0.000
DFP	0.500	0.264	0.358	0.358	0.002

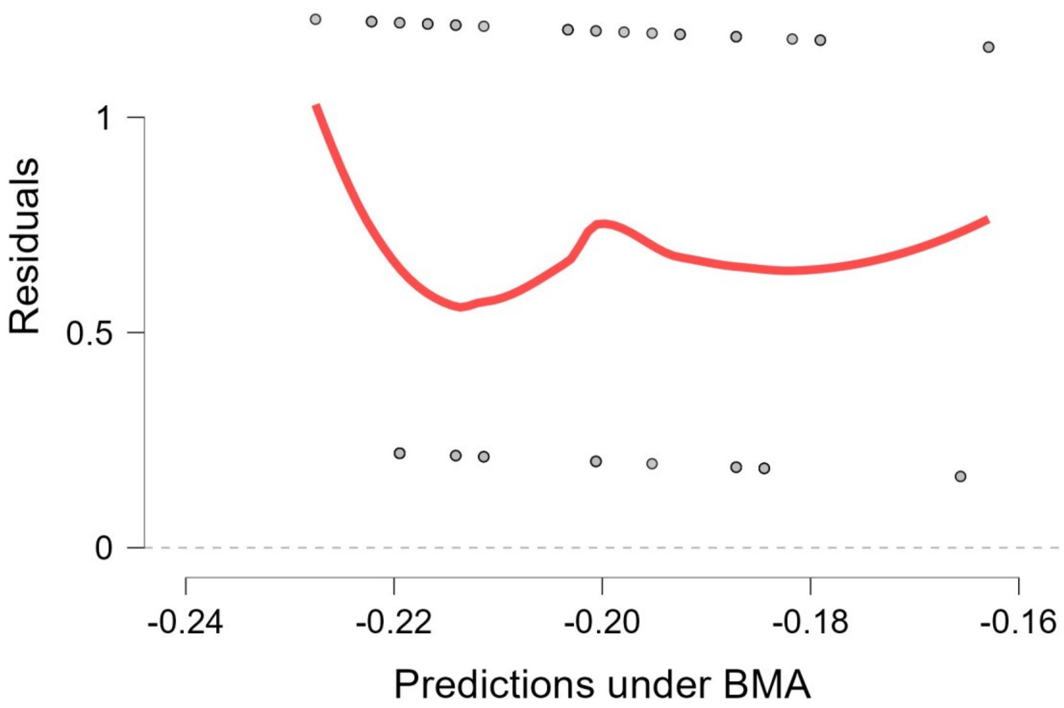
Posterior Summaries of Coefficients

								95% Credible Interval
Coefficient	P(incl)	P(excl)	P(incl|data)	P(excl|data)	$BF_{inclusion}$	Mean	SD	Lower
Intercept	1.000	0.000	1.000	0.000	1.000	−0.107	0.463	−0.805
DFP	0.500	0.500	0.264	0.736	0.358	−0.016	0.087	−0.242

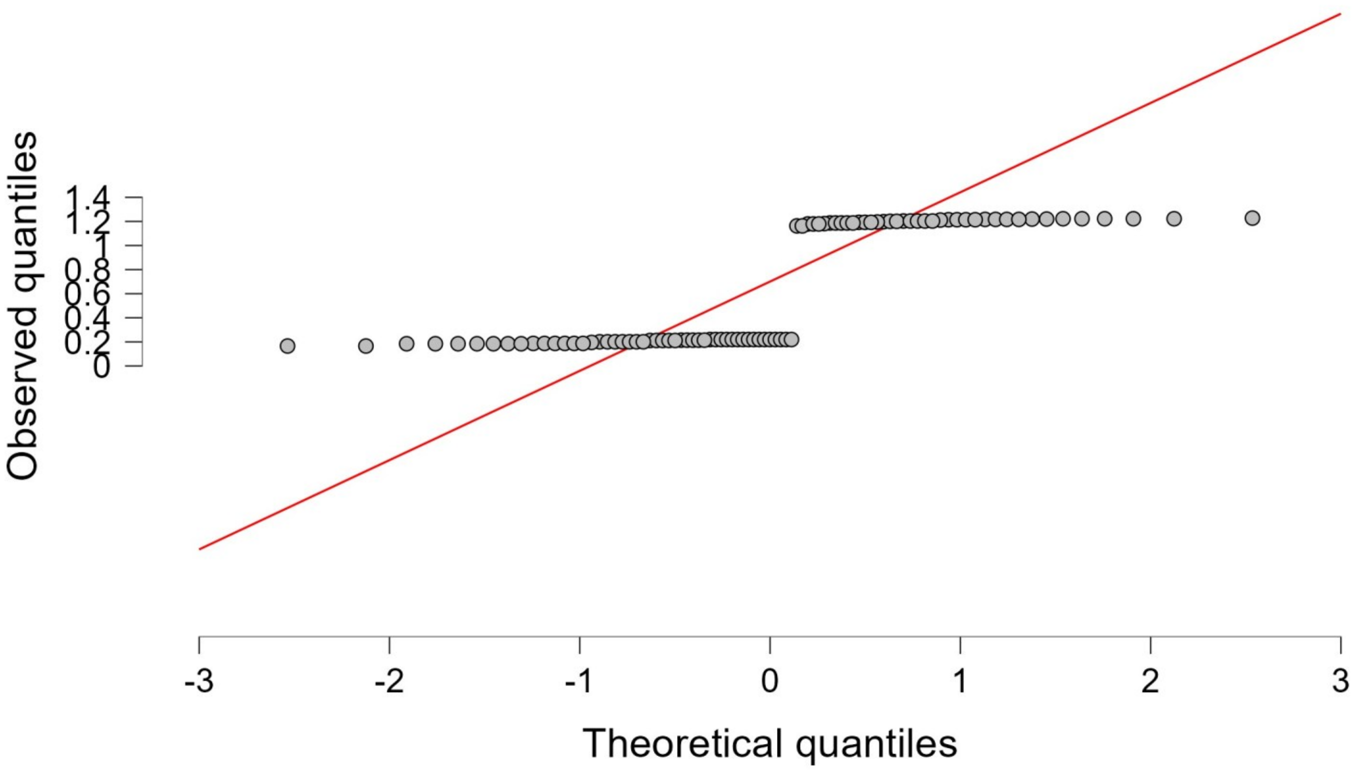
Posterior Coefficients with 95% Credible Interval



Appendix J: Residuals vs Fitted



Q-Q Plot



DV/Factor Descriptives

DV/Factor	Level	N
q33_loan_approved	0	49
	1	40

Covariate Descriptives

	N	Mean	SD
DFP	89	3.479	1.011

Appendix K: Bayesian Logistic Regression 3

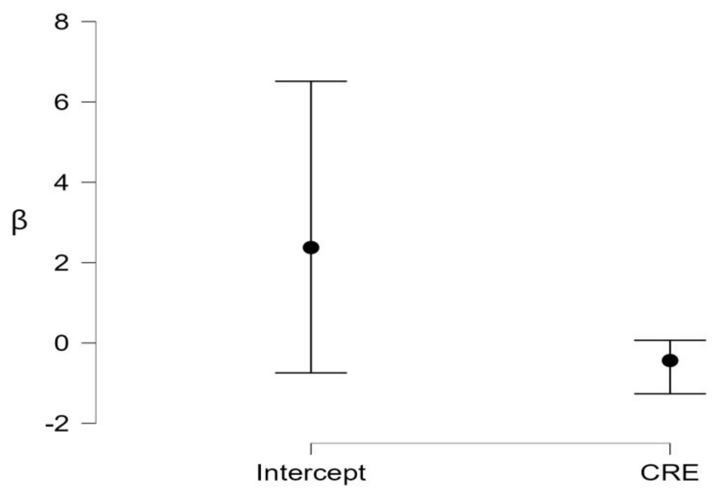
Model Comparison – q33_loan_approved

Models	P(M)	P(M|data)	BF_M	BF_{10}	R^2
CRE	0.500	0.702	2.354	1.000	0.043
Null model	0.500	0.298	0.425	0.425	0.000

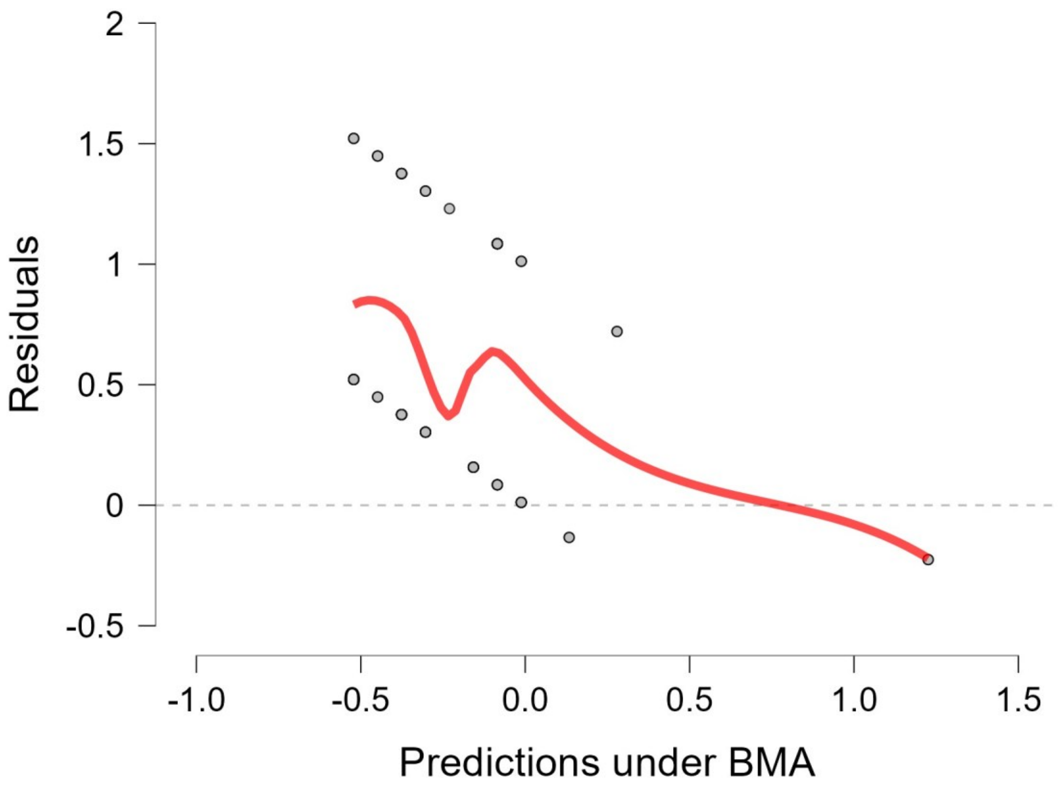
Posterior Summaries of Coefficients

								95% Credible Interval	
Coefficient	P(incl)	P(excl)	P(incl|data)	P(excl|data)	$BF_{inclusion}$	Mean	SD	Lower	Upper
Intercept	1.000	0.000	1.000	0.000	1.000	2.376	2.301	−0.744	6.514
CRE	0.500	0.500	0.702	0.298	2.354	−0.437	0.419	−1.264	0.066

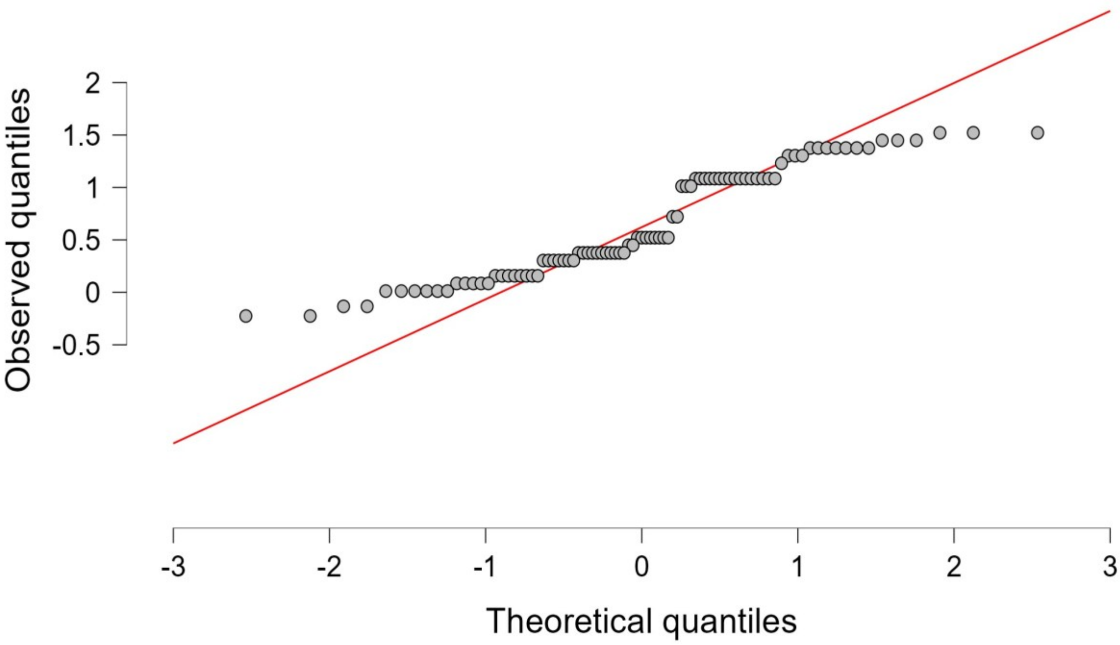
Posterior Coefficients with 95% Credible Interval



Appendix L: Residuals vs Fitted



Q-Q Plot



DV/Factor Descriptives

DV/Factor	Level	N
q33_loan_approved	0	49
	1	40

Covariate Descriptives

	N	Mean	SD
CRE	89	4.266	0.667

Appendix M: Bayesian Logistic Regression

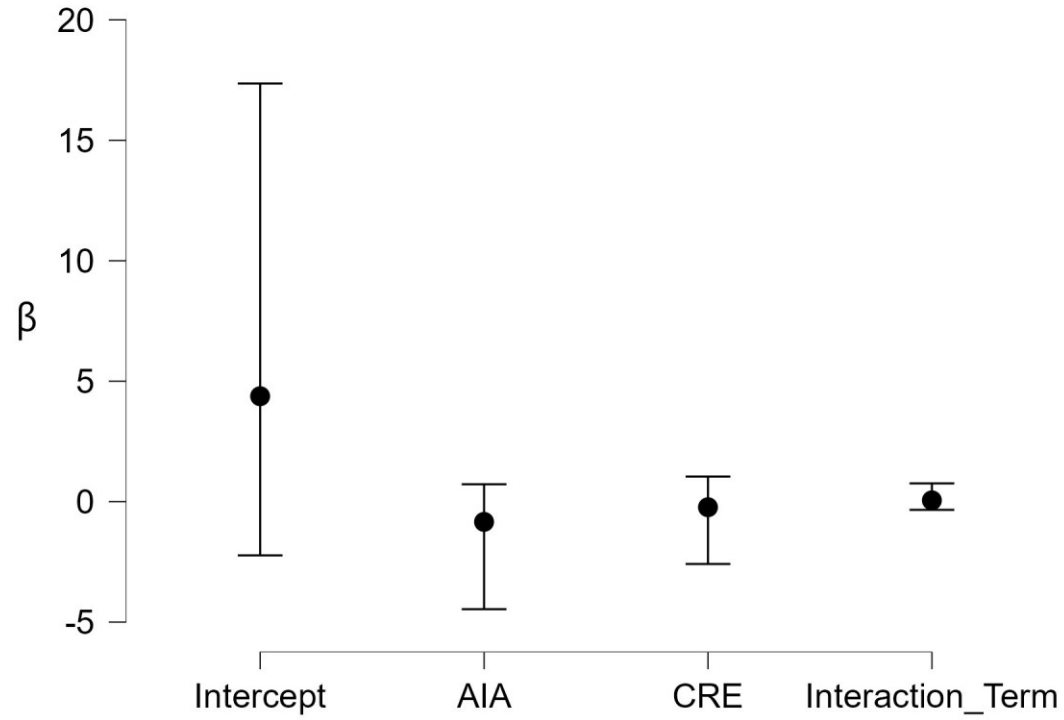
Model Comparison – q33_loan_approved

Models	P(M)	$P(M \mid data)$	BF_M	BF_{10}	R^2
Null model	0.250	0.062	0.198	1.000	0.000
AIA	0.083	0.252	3.712	12.197	0.077
AIA + CRE + Interaction_Term	0.250	0.244	0.970	3.938	0.085
Interaction_Term	0.083	0.147	1.891	7.093	0.066
AIA + Interaction_Term	0.083	0.096	1.166	4.633	0.077
AIA + CRE	0.083	0.091	1.100	4.396	0.077
CRE + Interaction_Term	0.083	0.059	0.691	2.857	0.068
CRE	0.083	0.049	0.563	2.354	0.043

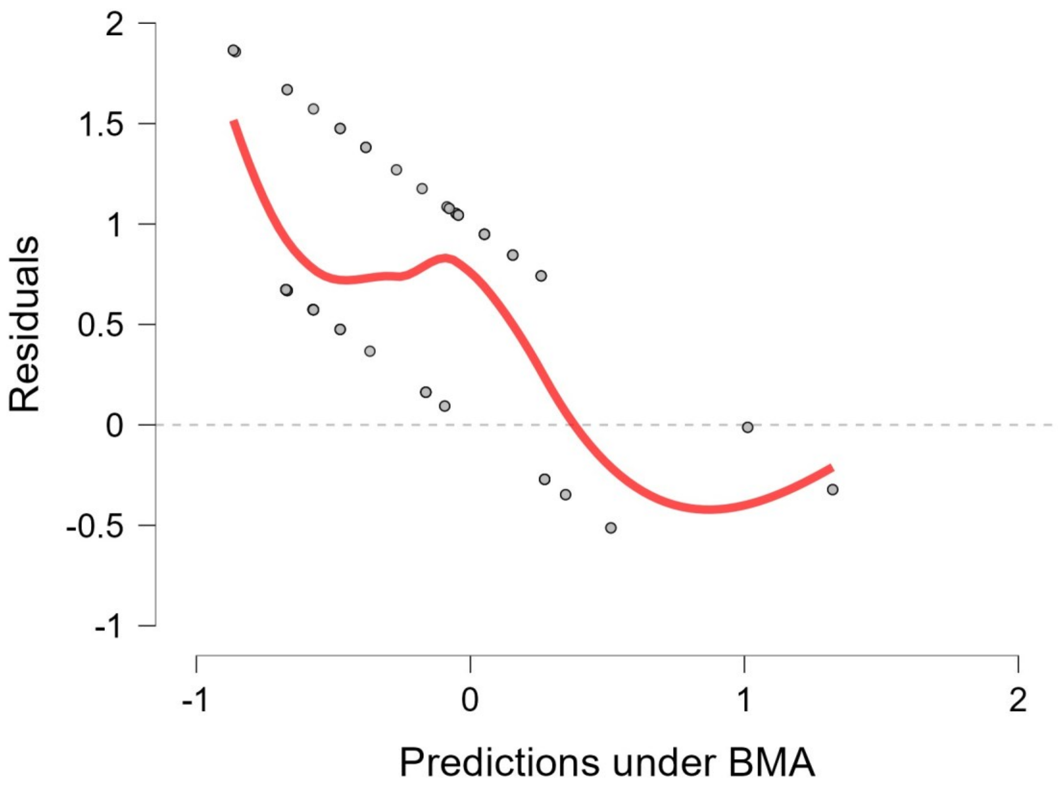
Posterior Summaries of Coefficients

								95% Credible Interval	
Coefficient	P(incl)	P(excl)	$P(incl \mid data)$	$P(excl \mid data)$	$BF_{inclusion}$	Mean	SD	Lower	Upper
Intercept	1.000	0.000	1.000	0.000	1.000	4.378	4.988	−2.229	17.360
AIA	0.500	0.500	0.683	0.317	2.159	−0.839	1.259	−4.463	0.723
CRE	0.500	0.500	0.443	0.557	0.796	−0.231	0.809	−2.587	1.042
Interaction_Term	0.500	0.500	0.546	0.454	1.203	0.055	0.264	−0.339	0.759

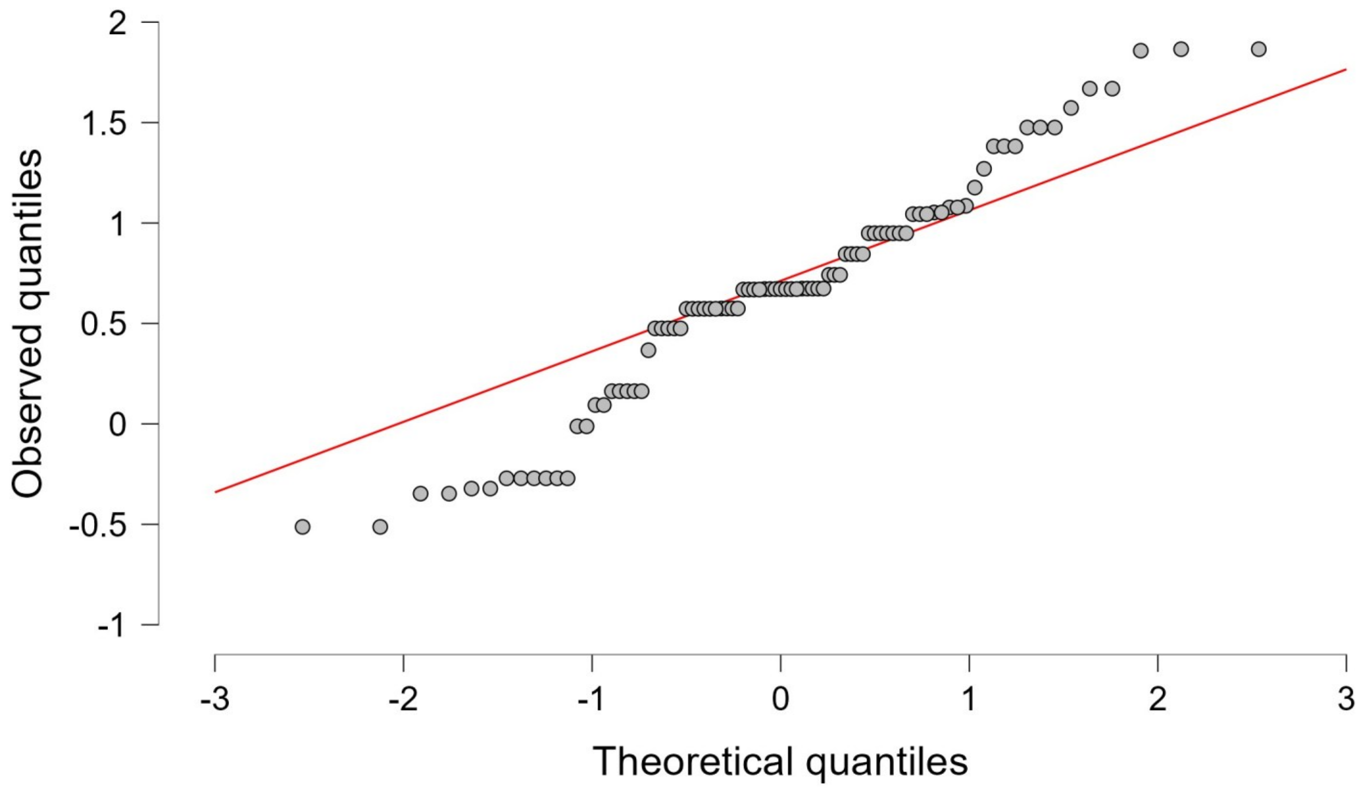
Posterior Coefficients with 95% Credible Interval



Appendix N: Residuals vs Fitted



Q-Q Plot



DV/Factor Descriptives

DV/Factor	Level	N
q33_loan_approved	0	49
	1	40

Covariate Descriptives

	N	Mean	SD
AIA	89	3.597	0.719
CRE	89	4.266	0.667
Interaction_Term	89	15.686	4.632