Bridging the Gap: Factors Driving Retail Analytics Adoption in Traditional Retail Businesses

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Abstract

This thesis investigates how South Africa's traditional retail sector adopts advanced analytics amid infrastructural, cultural, and economic constraints. Guided by the Technology-Organisation-Environment (TOE) framework and Diffusion of Innovations (DOI) theory, it addresses a critical gap in understanding the interplay of legacy systems, limited IT resources, and stringent regulatory demands on data-driven decision-making. A multi-case qualitative study of three large and mid-tier traditional retail chains in South Africa was conducted, involving 15 participants including store managers, IT directors, data analysts, marketing executives, and senior decision-makers. Findings highlight how outdated point-of-sale infrastructure, patchy internet connectivity, and frequent power outages impede real-time analytics. At the organisational level, siloed structures and staff concerns over job displacement slow adoption, despite growing leadership support for pilot projects and training programmes.

External forces, particularly the Protection of Personal Information Act (POPIA), socio-economic pressures such as high unemployment, and intense competition, further complicate large-scale analytics initiatives. Even promising solutions like loyalty cards and semi-automated storefronts have yielded uneven returns when confronted by crime risks, transient consumer behaviour, or landlord restrictions. Nonetheless, incremental deployments (e.g., "mobile-first" analytics and phased cloud migrations) emerge as viable stopgaps to overcome resource and connectivity challenges.

Findings underscore the importance of executive sponsorship, cross-functional collaboration, and targeted upskilling in fostering a data-centric culture. They also reveal that retailers can simultaneously advance sustainability goals, such as cutting waste and optimising energy usage, by harnessing predictive models that align with cost-saving strategies. Ultimately, this thesis argues that successful analytics adoption in emerging markets hinges on aligning technological ambitions with infrastructural realities and social imperatives. By integrating global best practices with localised approaches, retailers can enhance competitiveness, improve operational efficiencies, and contribute to inclusive, data-driven growth across South Africa's evolving retail landscape.

Keywords: Retail Analytics, Adoption Barriers, Technology-Organization-Environment Framework, Diffusion of Innovation, Traditional Retail, Data-Driven Culture, South Africa.

List of Abbreviations

The table below presents a comprehensive list of abbreviations and acronyms used throughout the thesis on Retail Analytics Adoption in South African Traditional Retail. These abbreviations provide clarity and consistency in referencing key terms, frameworks, and concepts.

Abbreviation	Full Term	Description
AI	Artificial Intelligence	A field of computer science that enables machines to learn and make decisions based on data.
API	Application Programming Interface	A set of protocols and tools that allow different software systems to communicate.
B2B	Business-to-Business	Transactions between businesses rather than between a business and consumers.
B2C	Business-to-Consumer	Transactions where businesses sell directly to individual consumers.
BI	Business Intelligence	Data-driven processes and tools used to analyse business performance.
CAPEX	Capital Expenditure	Expenses incurred by a business for acquiring or upgrading physical assets.
CRM	Customer Relationship Management	A system for managing interactions with customers to improve relationships and business outcomes.
CSV	Comma-Separated Values	A data format used to store tabular data in a plain-text format.
CSR	Corporate Social Responsibility	Business initiatives aimed at contributing to social and environmental well-being.
DOI	Diffusion of Innovations	A theory (Rogers, 2003) that explains how innovations spread through populations over time.
ERP	Enterprise Resource Planning	A type of software that integrates core business processes such as finance, supply chain, and HR.
ETL	Extract, Transform, Load	A data integration process that extracts data, transforms it, and loads it into a storage system.
FIFO	First In, First Out	An inventory management method where older stock is used or sold before newer stock.
IoT	Internet of Things	The interconnection of everyday devices via the internet, allowing data exchange and automation.
IT	Information Technology	The use of systems (e.g., computers, software) for storing, retrieving, and processing information.
KPI	Key Performance Indicator	A measurable value that indicates how effectively an individual or organisation is achieving key objectives.
LIFO	Last In, First Out	An inventory valuation method where the most recently added inventory is used first.
ML	Machine Learning	A subset of AI that enables systems to learn from data and make predictions without explicit programming.
NVivo	NVivo (Software)	A qualitative data analysis software used for coding and theme identification in research.
OPEX	Operational Expenditure	Ongoing expenses for running a business, such as rent, utilities, and salaries.
P&L	Profit and Loss Statement	A financial report that summarises revenues, costs, and expenses over a period of time.
POPIA	Protection of Personal Information Act	South African legislation that regulates data privacy and protection.

Abbreviation	Full Term	Description
POS	Point of Sale	The system where retail transactions occur, often including registers, barcode scanners, and payment processing tools.
RFM	Recency, Frequency, Monetary Value	A customer segmentation method based on past purchasing behaviour.
ROI	Return on Investment	A financial metric used to evaluate the efficiency or profitability of an investment.
SA	South Africa	A country in southern Africa, which serves as the context for this study.
SCM	Supply Chain Management	The management of the flow of goods and services from production to consumption.
SME	Small and Medium Enterprises	Businesses with limited revenue and workforce compared to large corporations.
SQL	Structured Query Language	A programming language used to manage and query relational databases.
TOE	Technology-Organisation-Environment	A framework (Tornatzky & Fleischer, 1990) used to assess technology adoption within firms.
UX	User Experience	The overall experience a user has when interacting with a system, particularly in terms of ease of use and satisfaction.

This table provides a quick reference guide to ensure terminological clarity and consistency throughout the thesis.

Table of Contents

Chapter 1: Introduction

1.1 Background

The retail industry was a cornerstone of the global economy, encompassing businesses ranging from e-commerce giants to traditional brick-and-mortar stores. Many physical retailers—particularly those with a minimal online presence—relied on older systems and manual approaches for tasks such as inventory management and demand forecasting. This scenario stood in sharp contrast to e-commerce and omnichannel retailers, which utilised advanced analytics to measure digital clickstream data, optimise dynamic pricing, and personalise customer experiences (Davenport & Harris, 2017; McKinsey & Company, 2019).

Retail analytics—spanning descriptive, predictive, and prescriptive methods—revolutionised the global retail landscape by enabling businesses to analyse sales trends, forecast demand, optimise store layouts, and refine marketing strategies (Delen & Zolbanin, 2018). In established markets, the integration of these analytics had become vital to maintaining competitive advantages, largely due to abundant data, seamless technological adoption, and widespread use of Artificial Intelligence (AI) and Internet of Things (IoT) solutions. For instance, predictive analytics allowed more precise inventory turnover planning, while prescriptive approaches informed strategic decisions such as store location optimisation (Bertsimas & Kallus, 2020).

By contrast, traditional retailers in developing economies like South Africa faced considerable barriers to analytics adoption. Outdated infrastructure, limited technological literacy, cultural resistance, and insufficient financial resources hindered efforts to address issues including inaccurate demand forecasting and suboptimal pricing (Naidoo & Gasparatos, 2019; Oki et al., 2021). Without data-driven strategies, these retailers risked losing ground to more agile competitors, including emerging e-commerce platforms and international entrants.

Given these global trends and the distinctive conditions in South Africa, this thesis investigated the drivers and barriers that shaped retail analytics adoption in the country's traditional retail sector. It explored how analytics-based tools could improve operational performance and bolster competitiveness in an increasingly data-driven marketplace.

1.2 Problem Statement

Despite ample evidence of the benefits of retail analytics, many traditional South African retailers remain hesitant to integrate such tools. This reluctance limits their capacity to address operational inefficiencies and respond effectively to changing consumer demands. While past research has focused on developed markets or e-commerce driven models, the distinct challenges of South Africa's brick-and-mortar stores remain underexplored.

Central to these challenges are persistent technological roadblocks. Many retailers rely on legacy systems incompatible with modern analytics solutions, and inadequate data governance or difficulty with system integration exacerbates the problem (Moloi et al., 2024). Moreover, organisational reluctance plays a major role: senior managers often hesitate to invest in analytics due to high perceived costs or limited awareness of its potential, and employees frequently lack the analytical expertise to use data insights effectively (Ridge et

al., 2015). External factors, such as economic instability, competitive pressure, and inconsistent infrastructure (e.g., unreliable internet), further compound these issues (Moloi et al., 2024).

However, while retail analytics provide significant opportunities to improve efficiency and decision making, it is crucial to recognise that their adoption is neither universally beneficial nor always feasible. Traditional retailers operating in resource-constrained environments must consider substantial trade-offs, including high initial investment costs, increased complexity, and potential operational disruption. Solutions developed in high-resource contexts may also fail to transfer effectively to markets characterised by infrastructural constraints and cultural resistance. By acknowledging these tensions, this study critically explores the specific conditions under which analytics adoption is both viable and strategically advantageous, rather than presuming it essential in all scenarios.

If not addressed, these multifaceted obstacles threaten to widen the performance gap between traditional South African retailers and their global counterparts. Accordingly, this study aims to identify key local barriers and propose context-sensitive strategies to facilitate effective analytics adoption in South Africa's traditional retail sector.

1.3 Research Purpose and Significance

Building on the problem statement, this research investigates the growing need for retail analytics in South Africa's traditional retail environment. Although retailers face pressures to enhance operations and customer engagement through analytics, they confront numerous barriers, including technological limitations, cultural resistance, and regulatory implications such as the Protection of Personal Information Act (POPIA) (Moloi et al., 2024; Ridge et al., 2015).

Using the Technology-Organisation-Environment (TOE) framework and the Diffusion of Innovations (DOI) theory, the study identifies key factors influencing analytics adoption. This dual-theory approach provides important insights for both academics and industry practitioners, particularly by contextualising global analytics strategies within the South African market (Moloi et al., 2024). Through qualitative case studies and interviews with key stakeholders, the research reveals the need to establish a robust data-driven culture. It emphasises that localising global analytics trends is crucial for South African retailers seeking to enhance competitiveness. Beyond individual businesses, widespread analytics adoption has the potential to improve customer satisfaction and contribute to sustainable economic growth (Ridge et al., 2015).

In addition to its practical implications, this research contributes theoretically by interrogating how the TOE and DOI frameworks perform in an emerging market context. Specifically, the empirical insights from this study allow for a refined understanding of how these models operate in settings marked by resource limitations, infrastructural instability, and distinctive socio-cultural influences. As such, the findings highlight conditions that may require adaptation or conceptual extension of the TOE and DOI frameworks to improve their relevance and explanatory power for mid-tier retailers operating in the global South.

By examining factors such as managerial support, organisational alignment, and stakeholder engagement, this study highlights pathways to effective analytics uptake. Socio-cultural

considerations—such as uneven internet access and customer trust—further underscore the sector's distinctive challenges (Moloi et al., 2024). Ultimately, the recommendations aim to support a realistic yet ambitious implementation strategy. In doing so, the study offers an incremental route to improved operational efficiency, while aligning organisational aims with evolving consumer expectations.

1.4 Research Questions and Objectives

To focus the investigation, this thesis posed one overarching research question and four sub-questions.

Overarching Research Question

What factors influences the adoption and successful implementation of retail analytics in South Africa's traditional retail sector?

Research Questions

1. What technological factors influences the adoption of retail analytics in South Africa's traditional retail sector?
2. How do organisational factors, such as leadership and employee readiness, impact analytics adoption?
3. What environmental factors, including market dynamics and regulatory pressures, shape the adoption of retail analytics?
4. How can traditional retailers address barriers to implement analytics successfully?

Research Objectives

1. To analyse technological barriers, such as legacy systems and integration challenges, that affected analytics adoption.
2. To evaluate the role of organisational readiness, leadership commitment, and employee skills in facilitating adoption.
3. To examine the influence of environmental pressures, such as competition and infrastructure constraints, on adoption decisions.
4. To propose actionable recommendations for traditional South African retailers to overcome adoption challenges and leverage analytics for competitive advantage.

1.5 Thesis Overview

This thesis is structured to provide a comprehensive exploration of the adoption of retail analytics in South Africa's traditional retail sector. It begins with Chapter 1: Introduction, which sets the stage by outlining the background, problem statement, research purpose, significance, and research questions and objectives. This chapter establishes the foundation for the study, emphasizing the importance of retail analytics and the barriers to its adoption in traditional brick-and-mortar retail businesses. Following this, Chapter 2: Literature Review delves into existing research on retail analytics adoption globally and locally, highlighting key theoretical frameworks such as the TOE framework and the DOI theory. It identifies gaps in the literature, particularly in the context of South African traditional retail, where systemic challenges and resource constraints hinder technological progress.

Chapter 3: Methodology outlines the research approach, which employs a qualitative case study method focusing on three large traditional retail chains in South Africa. The study collects data through semi-structured interviews with key stakeholders, including store managers and IT leaders,

and supplements this with secondary data from industry reports and internal documents. The TOE framework serves as a guiding lens for data collection and analysis, ensuring a structured examination of the technological, organizational, and environmental factors influencing adoption. The findings of this research are presented in Chapter 4: Findings, where the key results are organized around the research objectives, shedding light on the barriers and enablers of retail analytics adoption in the South African traditional retail sector.

In Chapter 5: Discussion, the findings are interpreted in the context of the research questions, theoretical frameworks, and existing literature, providing a deeper understanding of the complexities surrounding analytics adoption. Finally, Chapter 6: Conclusion synthesizes the study's contributions, highlights practical recommendations for industry stakeholders and policymakers, and outlines directions for future research. This structure ensures a logical progression of ideas, beginning with the identification of the research problem and culminating in actionable insights and scholarly contributions to the field of retail analytics adoption. The thesis provides a robust foundation for understanding and addressing the unique challenges faced by South Africa's traditional retailers in leveraging the transformative potential of retail analytics.

Chapter 2: Literature Review

2.1 Introduction

A well-structured literature review systematically examines and synthesizes current scholarship to identify key themes, theoretical underpinnings, and unresolved questions (Oosterwyk et al., 2019). In the context of South Africa's formal traditional retail—comprising established brick-and-mortar chains such as mid-tier to large supermarkets, department stores, and specialty retailers—the adoption of retail analytics has become increasingly important as the industry faces heightened competition, shifting consumer preferences, and digital innovations (Davenport & Harris, 2017; McKinsey & Company, 2023). Unlike fully modernized international chains like Walmart and Amazon or informal micro-retailers such as spaza shops, formal traditional retailers occupy a middle ground. While they benefit from legal licensing, sizable store footprints, and recognized brand identities, they often remain reliant on legacy systems, siloed data structures, and partially manual processes in areas such as inventory management, customer analytics, and supply chain coordination (Deloitte, 2021; Gupta & Rani, 2019). Consequently, while some retailers have adopted basic enterprise resource planning (ERP) or point-of-sale (POS) tools, the implementation of full-scale advanced analytics—such as predictive modeling and AI-driven personalization—remains inconsistent (Naidoo & Gasparatos, 2019).

To elucidate this adoption gap, this chapter explores the methodological basis of the literature search (Section 2.2) and examines the South African retail landscape, emphasizing the contrast between large, modern retailers and those still rooted in traditional structures (Section 2.3). It further discusses global benchmarks versus local realities, analyzing how international retail chains leverage analytics and why South African formal traditional retailers may lag (Section 2.4). To interpret adoption behaviors, the chapter introduces two principal theoretical frameworks: the Technology-Organization-Environment (TOE) model and the Diffusion of Innovation (DOI) theory (Section 2.5). A synthesis of key factors influencing analytics uptake follows in Section 2.6, culminating in an identification of research gaps and future research directions (Section 2.7). By the end of this chapter, a nuanced understanding of why South Africa's formal traditional retailers may struggle to

maximize data-driven strategies is established, offering an integrated framework to guide future research on bridging this analytics adoption divide.

2.2 Literature Search Strategy

2.2.1 Overview of Search and Inclusion Criteria

A systematic approach was adopted to ensure comprehensive coverage of existing research on factors driving retail analytics adoption in traditional retail businesses. The literature review process followed a structured methodology adapted from Günther et al. (2017) and Oosterwyk et al. (2019), ensuring that only peer-reviewed, methodologically rigorous, and empirically grounded studies were included. This process was conducted in four key phases: keyword formulation, initial screening, quality and relevance appraisal, and abstract review and refinement. Each phase contributed to refining the dataset, ultimately identifying the most relevant literature to inform this study.

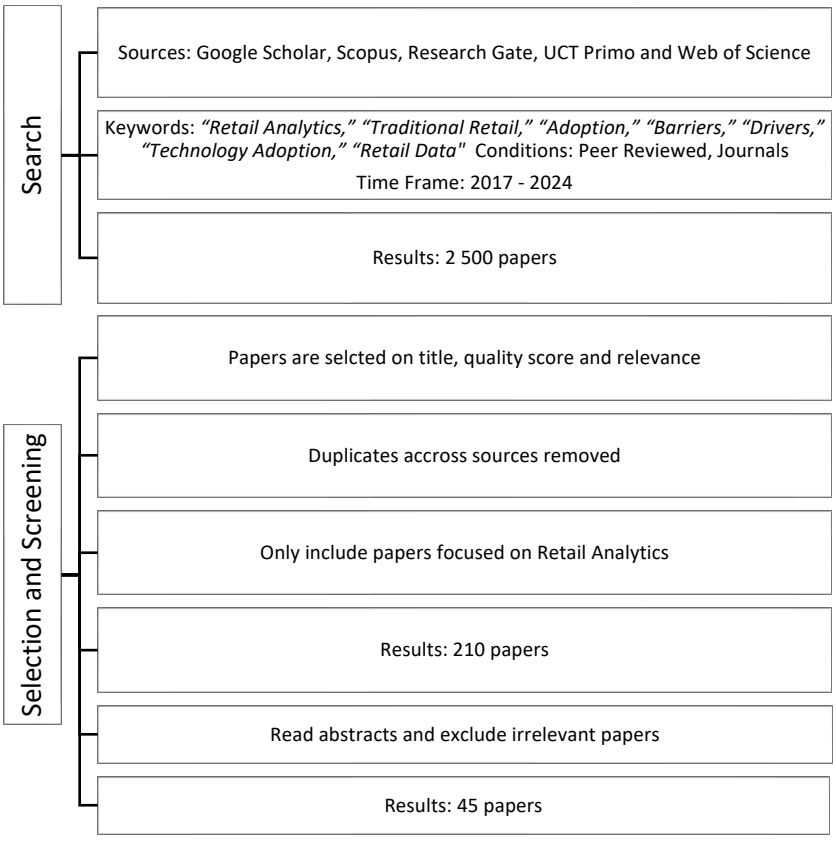

Figure 1: Process of literature review paper selection (after the fashion Günther et al., 2017, Oosterwyk's et al., 2019).

The first phase, keyword formulation, involved developing Boolean search strings that combined variations of key terms relevant to retail analytics, technology adoption, and traditional retail businesses. Keywords included: "Retail Analytics," "Traditional Retail," "Adoption," "Barriers," "Drivers," "Technology Adoption," "Retail Data," and "Retail Innovation." These terms were strategically linked using logical operators (AND, OR) to maximize relevance and ensure that studies spanning multiple related topics were captured. For example, searches were structured as ("Retail Analytics" OR "Retail Data") AND ("South Africa" OR "Emerging Markets") AND ("Adoption" OR "Implementation" OR

“Technology Integration”). The search was conducted across Google Scholar, Scopus, ResearchGate, UCT Primo, and Web of Science, as these databases index high-quality business and information systems research. To ensure current and relevant literature, the search was restricted to studies published between 2018 and 2024. This timeframe was chosen to reflect the latest advancements in retail analytics adoption, while allowing for the inclusion of foundational theoretical contributions where necessary.

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Following the keyword search, the second phase involved an initial screening to refine the dataset. The search yielded an initial 2,500 results, which underwent title and abstract filtering to assess their relevance to retail analytics adoption in traditional retail settings. At this stage, studies were included if they focused on retail analytics in brick-and-mortar stores, explicitly addressed adoption barriers and enablers, or applied established theoretical frameworks such as the Technology-Organization-Environment (TOE) model, Diffusion of Innovation (DOI) theory, or related models. Studies were excluded if they primarily discussed general digital transformation without specific reference to retail analytics, e-commerce-focused analytics, or technology adoption in non-retail contexts. Additionally, non-English studies and duplicates across databases were removed to enhance the accuracy and uniqueness of the dataset. By eliminating studies that did not align with the core research focus, this process reduced the dataset to approximately 210 papers.

In the third phase, a rigorous quality and relevance appraisal was conducted to ensure that the selected studies met methodological and contextual standards. This evaluation followed criteria adapted from Oosterwyk et al. (2019), emphasizing empirical rigor, theoretical depth, and direct applicability to retail analytics adoption. Studies were prioritized if they: (1) explicitly examined retail analytics adoption in traditional retail settings, (2) identified barriers, drivers, or enablers, (3) provided empirical data through case studies, surveys, or experimental research, and (4) included theoretical insights relevant to the adoption process. Conceptual and theoretical studies were included only if they applied structured analytical frameworks such as TOE, DOI, TAM, or UTAUT to retail analytics. Conversely, papers were excluded if they lacked empirical data, focused solely on multinational retail chains without relevance to traditional retail, or addressed technology adoption without discussing retail analytics explicitly. Through this process, studies that did not align with the specific research objectives were systematically excluded, further refining the dataset to 110 studies.

The fourth and final phase involved a detailed review of abstracts and full-text analysis to ensure alignment with the research scope. Abstracts were carefully examined to verify that each study contributed to the understanding of analytics adoption in traditional retail. Studies were further excluded if they lacked explicit discussions on adoption barriers, readiness, or contextual drivers. Papers focusing on large multinational retailers without any reference to traditional businesses were removed, as the study aims to explore the distinct challenges faced by mid-tier formal traditional retailers. Only studies with robust empirical findings, whether quantitative, qualitative, or mixed-methods, were retained to ensure a balanced representation of adoption challenges and enablers. After this final round of screening, 45 studies were deemed most relevant to the research.

In addition to the selected empirical studies, foundational texts were incorporated to provide essential theoretical grounding. Notably, Altman and Sabato (2007) on forecasting and inventory management, Sachs (2014) on digital transformation, and Davenport and Harris (2017) on analytics-driven competitiveness were retained for their seminal contributions to retail analytics. While predating the study's primary timeframe, these works complement recent empirical findings by offering critical conceptual insights.

The final selection of 45 studies ensures that the literature review remains methodologically rigorous and empirically validated. By integrating case studies, empirical analyses, and theoretical perspectives, this review establishes a robust foundation for examining retail analytics adoption in traditional businesses within South Africa and other emerging markets. The structured selection process minimizes bias and ensures that the dataset accurately represents the technological, organizational, and environmental factors influencing adoption. This systematic approach strengthens the academic rigor of the review, facilitating a comprehensive understanding of existing research while highlighting key gaps for future investigation.

2.3 Understanding Retail Analytics in South Africa

2.3.1 Nature of Traditional Retail

The South African retail sector is characterized by a dual structure, encompassing both informal and formal traditional retail enterprises. Informal retail, exemplified by spaza shops and independently owned small stores, typically operates outside formal regulatory frameworks, often relying on cash transactions and localized supply chains (Daugherty, Carrel-Billiard, & Biltz, 2018). In contrast, formal traditional retailers represent licensed and registered businesses that maintain brick-and-mortar operations while adhering to regulatory standards, including taxation and labor laws (Deloitte, 2021; The Supply Chain Lab, 2023).

Formal traditional retailers occupy a distinct position within the retail hierarchy. While they benefit from established brand identities—such as department stores and mid-tier supermarket chains—they frequently retain legacy operational practices, which may include outdated supply chain management methods and manual record-keeping (Granata, 2020). Despite implementing partial digital infrastructure, such as point-of-sale (POS) systems and basic enterprise resource planning (ERP) tools, their transition toward advanced retail analytics remains gradual and uneven (Naidoo & Gasparatos, 2019).

The spatial distribution of these retailers further differentiates them within the sector. Their presence in urban and peri-urban markets positions them between small-scale, micro-retailers

and large, fully modernized corporate entities—such as Shoprite and Woolworths, which have fully integrated digital and analytics-driven retail strategies (Deloitte, 2021). Despite this intermediary status, formal traditional retailers remain critical to the national retail economy, collectively accounting for an estimated 35–40% of the formal retail market (Deloitte, 2021). However, their continued reliance on legacy business models may present challenges to their competitiveness in an increasingly data-driven and digital retail landscape.

2.3.2 Digital Transformation Imperatives

Digital transformation within the retail sector typically involves upgrading processes, systems, and strategies to integrate digital tools such as point-of-sale (POS) data, cloud-based enterprise resource planning (ERP), and advanced analytics (Agrawal et al., 2022; Altman & Sabato, 2007; Adulyasak et al., 2022; Davenport & Harris, 2017). Even incremental digitization offers measurable benefits, including improved record-keeping, where electronic transaction logs replace manual counting to enhance sales accuracy (Chandramana, 2017). Real-time dashboards facilitate faster decision-making by enabling store managers to respond promptly to stockouts or shifting consumer trends (Proskurnina et al., 2021), while structured transaction data supports customer engagement initiatives, making loyalty schemes and targeted promotions more feasible (Chandramana, 2017).

Despite these advantages, digitization remains uneven among formal retailers, with many organizations relying on outdated financial or HR modules while lacking centralized data repositories for real-time analytics (Granata, 2020). Infrastructural constraints—such as load shedding and unreliable broadband connectivity—further impede real-time data capture, particularly in certain regions where digital access remains inconsistent (Proskurnina et al., 2021). As a result, digital transformation efforts often stall at the pilot stage or remain confined to select flagship stores, limiting scalability (Proskurnina et al., 2021). Beyond these technical and infrastructural hurdles, cultural inertia within traditional organizational structures presents an additional barrier to adoption (Davenport & Harris, 2017).

Senior management often relies on intuition-based decision-making or long-standing supplier relationships, perceiving analytics investments as costly or offering limited short-term payoffs (Chandramana, 2017). Employees, particularly those unfamiliar with data-driven workflows, may also view digitized systems as burdensome, especially if training initiatives are inadequate (Proskurnina et al., 2021). Therefore, achieving meaningful digital transformation in retail requires not only technical investments but also organizational shifts that promote data-driven decision-making and foster a culture of digital readiness (Proskurnina et al., 2021).

2.3.3 Regulatory Context

The Protection of Personal Information Act (POPIA) imposes robust obligations around data handling, storage, and usage, affecting formal retailers that collect customer data for analytics (Da Veiga & Swartz, 2023). Without specialized legal or compliance teams, some mid-level chains hesitate to expand analytics programs that require capturing personal identifiers. Encryption and secure data management add cost and complexity, fueling perceptions that advanced analytics may bring substantial compliance risk (Theys, 2020).

Unlike entirely informal shops—which may not engage with data legislation at all—or top-tier corporations with in-house legal departments, formal traditional retailers typically occupy

a middle ground of partial compliance and incremental data usage (Maraba & Da Veiga, 2024). They may, for instance, limit analytics to aggregated sales data rather than tracking individualized customer profiles. While this practice aligns with a low-risk stance, it restricts the potential for personalization or targeted marketing—key hallmarks of advanced retail analytics (Da Veiga et al., 2017).

2.4 Global Benchmarks vs. Local Realities

2.4.1 Global Success Stories in Retail Analytics

The role of data-driven decision-making in retail has been extensively documented, particularly in developed markets where advanced analytics tools are integral to business operations (Davenport & Harris, 2017). Prominent international retailers exemplify how predictive analytics, artificial intelligence (AI), and customer segmentation can enhance operational efficiency, inventory management, and consumer engagement.

One well-documented case is Walmart, which leverages advanced forecasting models and real-time inventory analytics to optimize stock levels across its extensive network of stores. By analyzing historical sales patterns and external factors—such as weather conditions and regional demand fluctuations—Walmart minimizes stockouts and excess inventory, thereby reducing carrying costs and improving supply chain responsiveness. The company's ability to dynamically adjust inventory strategies based on data insights serves as a benchmark for analytics-driven retail efficiency (Walmart's Transformation Through Data Analytics, 2023).

Similarly, Amazon has set a precedent in AI-driven personalization and dynamic pricing, utilizing sophisticated recommendation algorithms to drive cross-selling opportunities and customer retention. Through machine learning models, Amazon continuously refines its understanding of consumer preferences, optimizing product suggestions based on browsing behavior, purchase history, and contextual factors. This approach has significantly enhanced conversion rates and customer lifetime value, demonstrating the power of real-time data processing in shaping individualized shopping experiences (How Amazon Uses AI to Dynamically Adjust Prices, 2023).

Another notable example is Kroger, a leading grocery retailer that has pioneered the use of loyalty card data to develop highly granular customer segments. By analyzing purchase behavior at an individual level, Kroger tailors personalized promotions, optimizing pricing and product placement strategies to align with customer preferences. This data-centric approach enables the company to enhance customer engagement and retention, while also driving higher profitability through targeted marketing campaigns (Randhawa, 2019).

These cases collectively illustrate the strategic advantages of omnichannel integration and predictive analytics in modern retail. Research indicates that organizations effectively implementing data-driven decision-making frameworks can achieve greater operational efficiency, improved demand forecasting, and enhanced customer satisfaction (Naidoo & Gasparatos, 2019). The success of global retailers in adopting machine learning algorithms, real-time analytics, and AI-enhanced consumer insights underscores the transformative potential of advanced retail analytics, positioning data as a critical driver of sustained competitive advantage.

2.4.2 Contrasting Global vs. South African Environments

In contrast to developed markets benefiting from stable infrastructure, cloud capabilities, and robust supply chains, many formal retailers in South Africa encounter challenges such as inconsistent power supply, limited internet coverage, and budgetary constraints regarding large-scale IT investments (Granata, 2020; Ebrahim, 2022). These infrastructural limitations complicate the deployment of integrated analytics solutions that require continuous data connectivity and high computational capacity (Kshetri, 2021).

While global retail giants allocate substantial budgets to data science teams and advanced research and development, South African formal retailers often assign only modest resources to analytics initiatives (Randhawa, 2019). Organizational culture also plays a role; top-down management structures and reliance on traditional practices can impede the adoption of new tools (Davenport et al., 2023). Additionally, a shortage of skilled staff and limited technical training opportunities hinder the internal uptake of analytics platforms (Naidoo & Gasparatos, 2019).

Within the formal retail sector, disparities are evident: branches in affluent urban centers may partially adopt advanced tools, while stores in less-resourced regions struggle due to lower foot traffic, limited staff competencies, and infrastructural deficiencies (The Supply Chain Lab, 2023). This dual economy dynamic highlights the heterogeneity in digital readiness across the same retail chain, leading to inconsistent utilization of analytics (Ebrahim, 2022).

2.5 Theoretical Underpinnings: TOE and DOI

2.5.1 Technology-Organization-Environment (TOE) Framework

Developed by Tornatzky and Fleischer (1990), the TOE framework emphasises three dimensions of technology adoption: technological, organisational, and environmental.

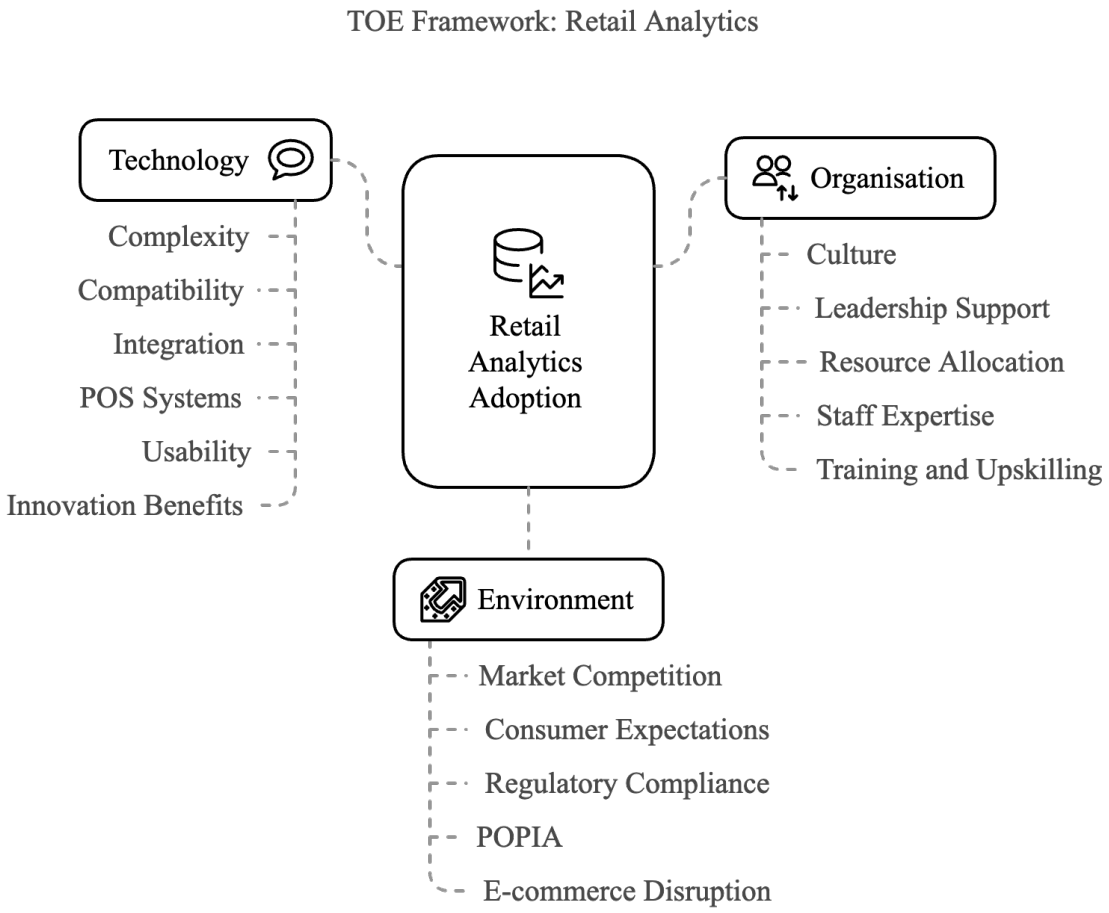

Figure 1: TOE Model. Adapted from Kumar, A., & Krishnamoorthy, B. (2020).

Technological Context: This dimension assesses the innovation's complexity, compatibility with existing systems, and perceived benefits or drawbacks. For formal traditional retailers, pertinent questions include whether analytics tools can seamlessly integrate with current point-of-sale (POS) setups and the user-friendliness of new interfaces (Chandramana, 2017).

Organizational Context: Factors such as internal culture, managerial support, resource availability, and staff expertise determine an organization's readiness for adopting new technologies. Retailers with strong executive advocacy for data-driven decision-making are more likely to allocate budgets and promote cross-functional collaboration. In contrast, the absence of such support may lead to underutilization of even robust IT capabilities (Kshetri, 2021; Davenport et al., 2023).

Environmental Context: External pressures, including market competition, consumer demands, and regulatory mandates, influence adoption decisions. In South Africa, compliance with the Protection of Personal Information Act (POPIA), competition from e-

commerce rivals, and the need to meet increasingly digitized consumer expectations are significant considerations within this context (Naidoo & Gasparatos, 2019).

2.5.2 Diffusion of Innovation (DOI) Theory

Rogers (1962) introduced the DOI theory to examine how innovations diffuse within social systems. Five attributes significantly affect adoption (Rogers, 1962; Randhawa, 2019):

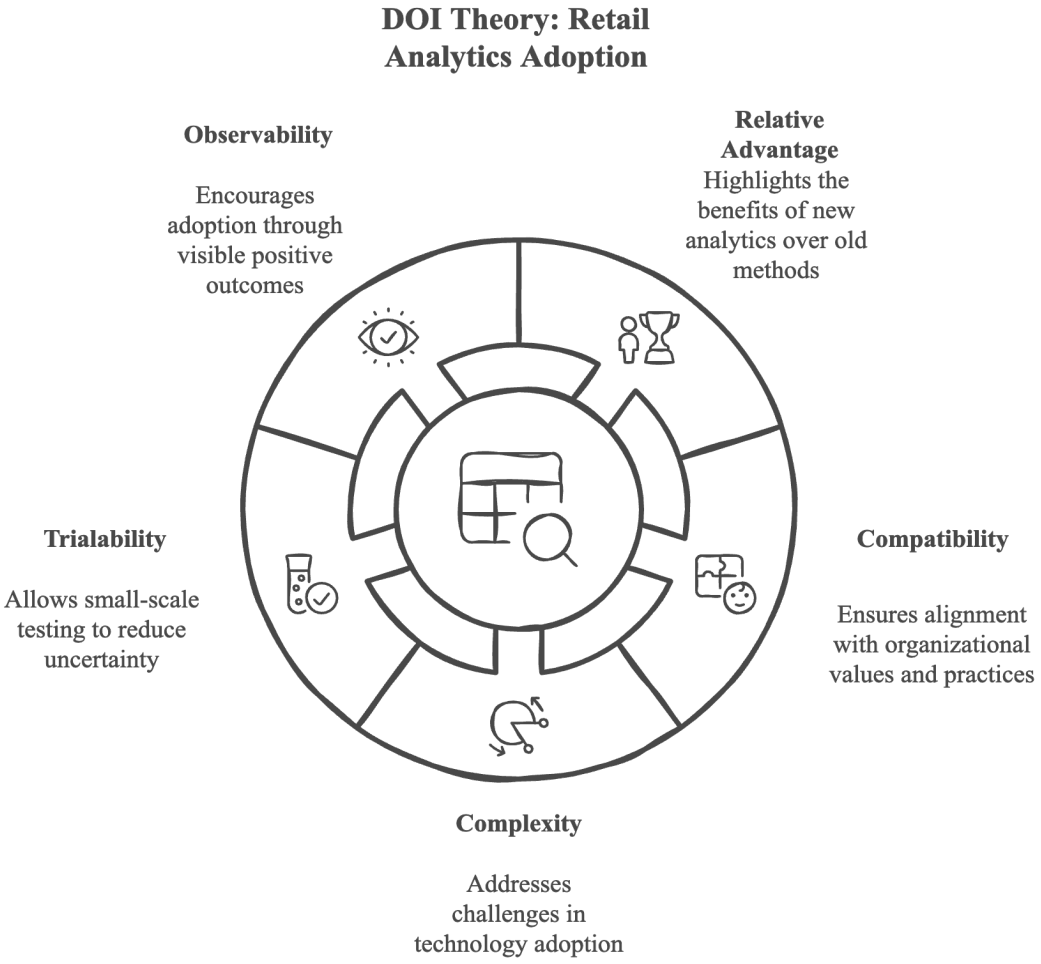

Figure 3: DOI Model. Adapted from Rogers, (1962).

The adoption of innovation is influenced by several key attributes, as outlined in Rogers' (1962) Diffusion of Innovations theory. Relative advantage refers to the perceived improvement an innovation offers over existing methods, making its adoption more likely when the benefits are clearly demonstrated. Compatibility describes how well the innovation aligns with an organization's values, norms, and established practices, with greater alignment leading to smoother integration (Chandramana, 2017). However, complexity can act as a barrier, as technologies perceived as difficult to understand or implement may deter staff from adopting them (Naidoo & Gasparatos, 2019). To mitigate this, trialability—the ability to test an innovation on a small scale before full implementation—reduces uncertainty and fosters confidence in its effectiveness (Gupta & Rani, 2019). Finally, observability plays a

crucial role, as the visibility of positive outcomes encourages broader adoption by demonstrating tangible benefits and influencing peers to adopt the innovation.

2.5.3 Integrating TOE and DOI

The TOE framework and DOI theory complement each other in providing a comprehensive understanding of analytics adoption. The TOE framework offers a macro-level view of the organisational, technological, and environmental factors influencing adoption, while the DOI theory provides a micro-level lens focused on how specific characteristics of innovations—such as complexity and compatibility—affect adoption decisions.

Key overlaps between the frameworks enhance their explanatory power. For example, the technological dimension of TOE aligns with DOI's emphasis on the role of complexity and compatibility in shaping adoption. Organisational readiness in the TOE framework mirrors the influence of opinion leaders and early adopters in DOI, highlighting how internal leadership and cultural dynamics drive innovation diffusion (Chandramana, 2017). These synergies illuminate the dual role of internal capabilities and the perception of innovation attributes in determining adoption success.

The TOE framework also extends beyond DOI by incorporating external pressures such as competition, regulatory demands, and socio-economic conditions into its environmental dimension. This broader perspective captures the unique challenges faced by South African retailers, such as compliance with POPIA and navigating infrastructural limitations, which DOI alone cannot fully address. For instance, while DOI focuses on internal innovation adoption, TOE's environmental lens reveals how market competition and regulatory frameworks influence readiness and decision-making.

Integrating these frameworks provides a holistic approach to understanding retail analytics adoption in South Africa. By combining macro- and micro-level insights, the study reveals how local retailers can address internal readiness, adapt to external pressures, and leverage innovation-specific traits to enhance adoption outcomes. This integrated perspective not only clarifies the complex interplay of factors shaping adoption but also offers actionable strategies for navigating South Africa's diverse and resource-constrained retail environment.

2.5.4 Critical Reflection on Frameworks and Construct Measurement

While the Technology–Organisation–Environment (TOE) framework and the Diffusion of Innovations (DOI) theory are widely used in technology adoption research, critical reflection is needed to clarify their respective contributions, conceptual boundaries, and areas of overlap. This study employs both frameworks to offer a comprehensive view of analytics adoption in traditional retail, but each theory brings distinct strengths that justify their combined use.

TOE is valued for its contextual breadth, particularly its ability to capture environmental influences such as infrastructure and regulation, which are especially relevant in the South African retail landscape. DOI, by contrast, provides more detailed insight into how innovation characteristics, including relative advantage, complexity, and compatibility, influence adoption decisions at the organisational or individual level. When used together,

these frameworks support a multi-level analysis that connects macro-level structural enablers with micro-level innovation perceptions.

Despite these advantages, several constructs overlap. For example, complexity in DOI relates to perceived difficulty of implementation, while technology readiness in TOE includes many of the same obstacles, such as skills shortages or lack of digital infrastructure. To avoid analytical duplication, this study applied the frameworks at different levels. DOI constructs were used to interpret perceptions of innovations themselves, while TOE constructs were applied to organisational capabilities and environmental conditions.

There is empirical support for combining these frameworks. Oliveira and Martins (2011) employed TOE and DOI together to assess e-business adoption in SMEs, and Baker (2012) used a similar approach in ERP implementation studies. However, these works also emphasise the importance of careful delineation to preserve theoretical clarity.

Another issue lies in how key constructs such as organisational readiness and employee resistance are defined and measured. Organisational readiness is variously assessed through indicators such as IT maturity, executive buy-in, or budget flexibility (Iacovou et al., 1995; Ghobakhloo and Tang, 2013), yet studies differ in how these elements are weighted or combined. Similarly, employee resistance is often linked to fear of redundancy, insufficient training, or digital fatigue, but lacks a unified framework for evaluation (Martins et al., 2016). This study responds to these gaps by capturing context-specific meanings through qualitative interviews, allowing participants' own interpretations of readiness and resistance to inform the analysis.

By clarifying the distinct roles of TOE and DOI, identifying overlap, and drawing on prior empirical usage, this study aims to contribute to a more rigorous and contextually grounded application of technology adoption theory in emerging market settings.

2.6 Factors Influencing Analytics Adoption

Retail analytics adoption within formal traditional retailers is influenced by a complex interplay of technological, organizational, and environmental factors. The TOE framework. provides a macro-level perspective on adoption readiness, while the DOI theory identifies how innovation-specific attributes—such as complexity, relative advantage, compatibility, trialability, and observability—shape individual decision-making.

This section integrates TOE and DOI to categorize key influences under three domains: technological, organizational, and environmental. It further introduces additional themes critical to formal retailers, such as data security, scalability, cost considerations, vendor ecosystems, and cross-functional collaboration.

2.6.1 Technological Factors

Data Integration and Legacy Systems

A defining characteristic of formal traditional retailers is their reliance on partially upgraded systems, where some branches operate modern point-of-sale (POS) and enterprise resource planning (ERP) software, while others still depend on legacy infrastructure (Gupta & Rani, 2019). This fragmentation hinders real-time data flow across departments, obstructing

analytics integration (Chandramana, 2017). The inability to synchronize sales, inventory, and customer data weakens analytics' potential to generate actionable insights (Davenport et al., 2023). Furthermore, system heterogeneity complicates IT modernization, as newer analytics solutions may be incompatible with legacy databases or require extensive middleware solutions (Naidoo & Gasparatos, 2019). DOI's compatibility factor underscores this as a major deterrent: if analytics platforms do not align with existing operations, adoption reluctance increases (Rogers, 1962).

Complexity of Advanced Tools

While some large retailers successfully leverage machine learning, AI-based recommendations, and predictive analytics, formal traditional retailers often struggle due to tool complexity and low digital literacy among frontline employees (Randhawa, 2019). The DOI complexity dimension posits that the higher the perceived difficulty of an innovation, the slower its adoption (Gupta & George, 2016). Many formal retailers also lack the technical expertise to interpret advanced analytics outputs, particularly when data visualization dashboards require statistical acumen (Naidoo & Gasparatos, 2019). This results in underutilization of analytics tools despite their presence in the organization (Davenport et al., 2023). To mitigate complexity, scholars advocate for modular analytics systems—allowing phased implementation—ensuring that store managers can gradually integrate analytics into decision-making without overwhelming them (Chandramana, 2017).

Compatibility with Operational Routines

Analytics platforms must seamlessly align with existing workflows—inventory checks, procurement cycles, workforce scheduling, and promotional planning—to gain organizational buy-in (Randhawa, 2019). If analytics requires significant changes in daily routines or creates additional administrative burdens, adoption resistance increases (Rogers, 1962). For example, retailers operating across multiple branches may struggle to maintain uniformity in data collection, limiting analytics' ability to provide meaningful comparisons (Gupta & Rani, 2019). Compatibility issues thus extend beyond software and touch upon operational standardization, which varies across retailers (Daugherty et al., 2018).

Scalability and Future-Proofing

Retailers considering long-term investments in analytics must assess whether solutions are scalable and adaptable to future technological advancements (Ebrahim, 2022). While smaller-scale implementations (e.g., single-store pilots) may appear feasible, scaling analytics solutions across multiple locations presents challenges, particularly where IT infrastructure differs across branches (Granata, 2020). Firms with rigid system architectures often face high switching costs, leading to vendor lock-in and discouraging analytics adoption (Walker & Brown, 2019). Scalability considerations thus impact whether retailers pursue analytics integration gradually or defer modernization altogether (Naidoo & Gasparatos, 2019).

Data Security and Privacy Concerns

Retailers handling large volumes of customer transactions must ensure that analytics solutions align with data protection regulations such as POPIA (Davenport et al., 2023). Advanced analytics—particularly personalized marketing and predictive customer profiling—requires secure data storage and compliance frameworks, which can elevate initial

implementation costs (Granata, 2020). Data security concerns also include cyber risks, particularly when retailers migrate from on-premise systems to cloud-based analytics (Naidoo & Gasparatos, 2019). Organizations wary of security breaches or third-party data sharing risks often limit analytics deployment to aggregated sales reports, avoiding more granular consumer insights (Gupta & George, 2016).

2.6.2 Organizational Factors

Leadership Commitment and Vision

Executive support is one of the most cited enablers of analytics adoption (Kshetri, 2021). If top management perceives clear advantages (e.g., enhanced demand forecasting, optimized stock levels), they are more likely to secure budget allocations and champion cross-functional collaboration (Oki, Tengeh, & Popoola, 2021). Conversely, where leadership is risk-averse or lacks digital literacy, analytics projects remain stagnant or underfunded (Davenport, Harris, & Shapiro, 2023). Retailers that prioritize data-driven decision-making at the board level tend to exhibit higher adoption success (Randhawa, 2019). DOI's observability dimension reinforces this: if management sees competitors benefiting from analytics, they are more inclined to initiate pilot projects (Rogers, 1962).

Employee Readiness and Digital Literacy

While leadership may endorse analytics, employee reluctance often impedes adoption (Naidoo & Gasparatos, 2019). Formal retailers span multiple departments—merchandising, finance, logistics, and store operations—each with distinct data needs and analytical skills (Randhawa, 2019). If frontline staff fail to see how analytics streamlines their tasks, they remain disengaged or actively resist change (Gupta & George, 2016). For instance, sales staff accustomed to manual ordering methods may struggle to trust demand-prediction models, undermining their utility (Davenport, Harris, & Shapiro, 2023).

Cross-Functional Collaboration and Siloed Data Culture

Formal retailers often suffer from data silos, where analytics remains confined to specific teams (e.g., marketing, finance) rather than becoming an organization-wide tool (Kshetri, 2021). Fragmentation between store-level operations and head-office analytics teams further exacerbates knowledge asymmetry, preventing insights from reaching decision-makers (Walker & Brown, 2019). Collaboration across departments and store locations is necessary for analytics to drive holistic retail strategy, yet siloed cultures restrict adoption, aligning with TOE's organizational dimension (Davenport, Harris, & Shapiro, 2023).

2.6.3 Environmental Factors

Market Competition and Consumer Expectations

As e-commerce and modern retail chains expand, formal traditional retailers face increasing pressure to optimize their business models (Bertsimas & Kallus, 2020). Consumers expect real-time availability, personalized discounts, and omnichannel experiences, compelling retailers to adopt data-driven strategies (Daugherty et al., 2018).

However, market competitiveness varies geographically. Urban retailers, exposed to greater price competition and digital-native consumers, tend to adopt analytics faster than retailers in rural or peri-urban regions (Gupta & Rani, 2019). This aligns with DOI's observability principle—when competitors successfully leverage analytics, late adopters experience greater pressure to modernize (Rogers, 1962).

Vendor Ecosystem and External Partnerships

Retail analytics adoption is also contingent upon the availability of trusted technology partners (Naidoo & Gasparatos, 2019). If retailers have reliable vendors offering cost-effective, localized solutions, they are more likely to explore data-driven decision-making (Davenport et al., 2023). However, dependence on international software providers can complicate implementation, as these platforms may not cater to South African market conditions (Kshetri, 2021).

Regulatory Pressures (POPIA) and Compliance Burdens

As discussed, POPIA compliance introduces additional layers of complexity (Granata, 2020). The need for customer consent management, data encryption, and audit readiness can discourage retailers from collecting individualized transaction data, restricting their ability to develop robust customer insights (Davenport et al., 2023). Retailers operating across multiple jurisdictions may face varying interpretations of compliance mandates, further complicating adoption efforts (Walker & Brown, 2019).

2.7 Synthesis and Research Gaps

2.7.1 Key Barriers and Emerging Contrasts

A significant portion of the literature underscores that South Africa's formal traditional retail sector contends with a multifaceted set of barriers—spanning legacy IT infrastructures, organizational inertia, and regulatory constraints—that impede robust analytics adoption (Granata, 2020; Kshetri, 2021). Reliance on outdated systems and siloed data practices complicates real-time data integration, while cultural resistance and minimal technical expertise limit meaningful analytics usage for daily decision-making (Randhawa, 2019; Chandramana, 2017). At the environmental level, researchers cite both intensified e-commerce competition and the Protection of Personal Information Act (POPIA) as compounding factors, particularly for mid-tier retailers lacking large compliance teams (Naidoo & Gasparatos, 2019; Davenport et al., 2023).

Despite these impediments, other studies highlight substantial opportunities to enhance operational efficiency, profitability, and customer engagement via analytics-driven approaches (Davenport & Harris, 2017; Bertsimas & Kallus, 2020). Scholars referencing global exemplars (e.g., Walmart's predictive modeling, Amazon's AI-powered personalization) illustrate how data-driven innovations can yield substantial competitive advantages (Davenport & Harris, 2017; Gupta & Rani, 2019). Yet, adopting such global "best practices" is complicated by local constraints around infrastructure, culture, and data privacy regulations (Naidoo & Gasparatos, 2019; Gupta & George, 2016). These contrasting views reveal a tension in the literature: while some advocate for pilot-driven, incremental adoption to accommodate local resource limitations, others posit that comprehensive system overhauls may be needed to realize full-scale benefits (Chandramana, 2017; Randhawa, 2019).

2.7.2 Underexplored Areas and Methodological Gaps

Despite convergent themes on the value of analytics and the viability of the TOE–DOI framework, several research gaps persist. First, empirical studies commonly focus on either highly advanced retail chains with mature analytics ecosystems or micro/informal outlets with rudimentary digital tools, leaving mid-tier formal retailers largely underexamined (Walker & Brown, 2019; Chandramana, 2017). This "in-between" category—licensed retailers operating multiple stores but still reliant on traditional processes—lacks detailed case analyses on how to incrementally unify legacy databases or integrate data dashboards across diverse branches (Gupta & Rani, 2019; Randhawa, 2019).

Second, longitudinal perspectives remain scarce. Existing literature often provides static snapshots, overlooking how organizational behaviors and adoption barriers evolve over time, especially when initial "quick wins" from pilot analytics might eventually scale into enterprise-wide strategies (Oki, Tengeh, & Popoola, 2021). There is also limited examination of how comprehensive adoption pathways compare to incremental ones in delivering sustainable analytical capabilities (Naidoo & Gasparatos, 2019; Chandramana, 2017).

Third, data privacy and compliance tensions—particularly under POPIA—are widely acknowledged but seldom scrutinized in depth (Granata, 2020). Although some studies note that stringent regulations can discourage retailers from gathering individualized data, others suggest partial anonymization or minimal data collection as viable compromises, albeit with uncertain impacts on personalization or loyalty programs (Davenport et al., 2023; Kshetri, 2021). This diverging discourse points to a need for deeper empirical exploration into the operational interplay of compliance frameworks, cultural acceptance, and business-driven analytics (Randhawa, 2019).

2.7.3 Way Forward for Empirical Investigation

Integrating Research Gaps A and Research Gaps B reveals the importance of contextual, empirical studies that examine how technological, organizational, and environmental influences (TOE) combine with innovation attributes (DOI) under real-world constraints. While the literature concurs on the transformative potential of analytics, its actualization in formal traditional retailers hinges on localized strategies addressing infrastructural limitations, workforce skill deficits, and regulatory strictures (Naidoo & Gasparatos, 2019; Gupta & George, 2016). The lack of in-depth, longitudinal investigations that track these organizations' adoption journeys—involving pilot rollouts, cultural shifts, compliance adjustments, and scaling phases—further underscores a pressing need for practical implementation frameworks (Chandramana, 2017; Walker & Brown, 2019).

Accordingly, future research may profit from multi-case analyses or phased, longitudinal designs that detail how mid-tier South African retailers navigate each stage of analytics uptake, from bridging legacy systems to tackling POPIA-compliance hurdles. Such work would illuminate whether incremental or comprehensive adoption processes lead to more sustainable outcomes, and how employee buy-in evolves with each observable success. By clarifying the specific enablers and obstacles at each phase, scholars can refine both TOE and DOI theories in an emerging-market context, ultimately bridging the gap between global best practices and local application (Randhawa, 2019; Kshetri, 2021).

Chapter 3: Methodology

3.1 Research Design

The research design outlines the methodological framework for this study, focusing on the adoption of retail analytics within South Africa's traditional retail sector. This design emphasizes a qualitative case study approach to explore the nuanced, context-specific challenges and opportunities faced by traditional retailers in a resource-constrained environment. The selected methods aim to provide a rich, in-depth understanding of the factors influencing the adoption of retail analytics, combining primary and secondary data sources to ensure a comprehensive analysis.

3.1.1 Philosophical Underpinnings

Ontological Stance

The ontological stance adopted here is constructivist, which holds that reality is socially constructed and context-dependent (Lincoln & Guba, 1985). In exploring retail analytics adoption, a constructivist perspective acknowledges how individuals in different roles may interpret factors such as technological infrastructure, leadership commitment, and external pressures in various ways. By recognising that these factors are not strictly objective but instead are shaped by social and organisational contexts, the research seeks to capture the lived and often fluid realities of analytics adoption. This focus on context-sensitive meanings would be less feasible under a positivist ontology, which presupposes a stable and measurable reality existing independently of human perceptions (Easterby-Smith, Thorpe, Jackson, & Jaspersen, 2018). Since the study is designed to explore subjective experiences in depth, constructivism is deemed the most appropriate philosophical foundation.

Epistemological Stance

Aligned with its constructivist ontology, the study takes an interpretivist epistemology, emphasising the understanding of subjective meanings and the influence of contextual factors on how individuals perceive phenomena (Crotty, 1998). Interpretivism diverges from a positivist or post-positivist approach by seeking to uncover how stakeholders in retail environments—such as store managers, IT directors, and executives—make sense of analytics tools and their implications. This orientation is valuable for shedding light on how internal beliefs, cultural dynamics, and organisational structures affect decisions about whether, why, and how analytics tools are adopted. By prioritising qualitative inquiry and inductive reasoning, the study can capture the interpretive nuances that typically remain hidden in approaches that rely heavily on measurement and hypothesis testing (Neuman, 2014).

3.1.2 Research Approach and Philosophical Paradigm

This research aligns with an interpretivist paradigm, which prioritises the exploration of subjective experiences and contextual influences. Unlike positivism, which seeks to uncover objective truths through standardised measurement, interpretivism allows the researcher to investigate how individuals and organisations perceive, interpret, and respond to the adoption of analytics tools. This paradigm is particularly appropriate for understanding complex

decision-making processes within traditional retail environments, where technological, organisational, and environmental factors interact in nuanced ways.

Building on this philosophical foundation, the study adopts an abductive approach to qualitative inquiry. Abduction combines elements of inductive reasoning, where patterns and themes emerge from empirical data, with deductive logic, where theoretical frameworks guide interpretation. Unlike pure induction, which avoids predefined constructs, or pure deduction, which tests specific hypotheses, abduction supports an iterative dialogue between data and theory to produce plausible explanations (Timmermans and Tavory, 2012).

While the study initially embraced inductive principles to allow for unanticipated insights to emerge from participant narratives, it also employed the Technology–Organisation–Environment (TOE) framework and Diffusion of Innovations (DOI) theory as sensitising constructs. These frameworks informed both the data collection instruments and the analytical process. This iterative engagement between theory and data aligns with what Dubois and Gadde (2002) describe as "systematic combining," a defining feature of abductive reasoning.

By blending theory-informed coding with context-specific insights, this approach strengthens the study's ability to produce both empirical depth and theoretical refinement. This is especially relevant in emerging market contexts like South Africa's retail sector, where existing technology adoption models must often be adapted to fit infrastructural constraints, resource limitations, and unique socio-cultural dynamics.

3.1.3 Qualitative Case Study Approach

Building on the interpretivist and inductive underpinnings, this study employs a qualitative case study design to explore how traditional retailers in South Africa adopt retail analytics. As advocated by Yin (2018), case studies are particularly suitable for investigating "how" and "why" questions embedded in real-life contexts, especially where multiple factors and variables interact in ways not easily captured by experimental or survey-based methods. This design facilitates an in-depth examination of organisational processes, staff attitudes, technology infrastructures, and external pressures that shape adoption decisions.

A qualitative approach is prioritised over a quantitative or mixed-methods approach because the primary interest lies in obtaining rich, contextual insights into participants' interpretations and experiences, rather than obtaining broad statistical generalisations (Creswell & Creswell, 2018). Quantitative strategies could provide useful measurements or correlations but would likely overlook nuances such as cultural resistance, varying leadership styles, or the subjective apprehensions of staff. Meanwhile, a mixed-methods design might integrate aspects of breadth and depth but would require resources and data collection strategies not readily aligned with the current project's focus on deeply contextual narratives (Morgan, 2007). Consequently, a qualitative case study emerges as the most coherent strategy for understanding complex adoption phenomena in a context-specific manner (Stake, 1995).

3.1.4 Case Selection and Scope

This study focuses on three formal, traditional retail chains in South Africa, each characterised by an extensive physical store footprint, structured supply chains, and differing levels of technological integration. These firms were purposively selected to allow for

analytical variation in the adoption of retail analytics and to align with the interpretivist goals of the research.

The selection of large and mid-tier formal retailers is deliberate. These businesses represent a critical segment of the national retail economy where data-driven decision-making has the potential to improve operational efficiency and enhance competitiveness. Larger formal retailers typically possess structured IT departments, established decision-making hierarchies, and greater access to financial and human capital, all of which enable the exploration and implementation of advanced analytics tools. The study aims to examine how these capabilities interact with contextual constraints in shaping the uptake of retail analytics.

A key scoping decision was to exclude smaller or informal retailers. While informal retail plays a significant role in South Africa's economy, it operates under markedly different conditions – including cash-based transactions, low digital penetration, and informal decision-making structures. The theoretical frameworks underpinning this study, particularly the Technology–Organisation–Environment (TOE) framework and Diffusion of Innovations (DOI) theory, emphasise structured organisational processes and systemic influences on technology adoption. Applying these frameworks to the informal sector, where such structures may not exist, would have compromised the coherence and applicability of the research.

Moreover, limiting the study to three firms strikes a deliberate balance between depth and breadth. A single-case study could offer rich contextual insight but may be overly idiosyncratic, limiting transferability. Conversely, incorporating a broad range of cases – including informal businesses – might dilute the depth of analysis due to divergent variables. By focusing on three firms with varying geographic reach, digital maturity, and strategic orientation, the study enables meaningful cross-case comparison while preserving the contextual richness essential to qualitative inquiry.

The firms were selected based on several criteria, including their type and size (large or mid-tier), geographic representation, accessibility for semi-structured interviews, and varying levels of digital and analytics maturity. Firm A is a national retail chain characterised by legacy point-of-sale systems, limited analytics infrastructure, and a conservative stance towards digital transformation. Operating primarily in peri-urban and rural areas, this firm faces significant challenges related to infrastructure and workforce skills. Firm B is a regionally based mid-tier retailer that is currently piloting a cloud-based analytics solution. It occupies a transitionary position, demonstrating moderate organisational support for analytics initiatives alongside ongoing efforts to build internal data capabilities. In contrast, Firm C is an urban-based retailer with relatively advanced analytics integration and a dedicated internal data team. Despite continuing to navigate regulatory and connectivity constraints, this firm actively invests in predictive modelling and loyalty programme optimisation. The deliberate selection of these three firms provides a valuable cross-section of the traditional retail sector, reflecting distinct organisational contexts and stages of analytics maturity.

3.2 Data Collection Methods

3.2.1 Sampling Strategy

A purposive sampling approach was adopted to select participants with expertise and direct involvement in the adoption of retail analytics. This method ensures the inclusion of

individuals who are best positioned to provide rich and relevant insights, aligning with the study's focus on understanding specific challenges and drivers (Saunders, Lewis, & Thornhill, 2019). Participants were drawn from three large traditional retail chains in South Africa, chosen for their representativeness of the sector's diversity in terms of operational scale, market focus, and geographical reach.

The sample comprises 15 participants, including store managers, IT leaders, and senior decision-makers responsible for strategic and technological initiatives. These roles were chosen to capture a broad spectrum of perspectives, reflecting both high-level strategic priorities and operational challenges in implementing retail analytics. Specifically, the sample included IT Directors, CEOs, Data Scientists, Executive Leaders, Marketing Directors, and Customer Insights Managers. This range allowed the study to encompass views from those driving technological innovation and adoption to those evaluating its strategic alignment and business impact. The inclusion of Sustainability Officers and Financial Analysts further broadened the analysis by integrating insights into environmental initiatives and budgeting priorities. For more details on the roles and key focus areas of the participants, see Appendix 2.

The sample size of 15 participants is deemed sufficient to capture these varied perspectives across key organizational roles while remaining manageable for in-depth qualitative analysis (Yin, 2018). Participants were selected based on their active involvement in analytics-related decision-making and implementation processes, ensuring that the data collected is directly relevant to the research objectives.

The integration of the DOI theory into the sampling strategy is significant, as it emphasizes the role of early adopters and opinion leaders in driving innovation diffusion (Rogers, 1962). By including participants who influence or shape their organizations' technology adoption processes—such as Chief Data Officers and Analytics Department Leads—the study was able to explore how these roles impact the diffusion of retail analytics within the traditional retail context.

3.2.2 Interview Process and Justification

Semi-structured interviews

Semi-structured interviews were the primary method of data collection, providing the flexibility needed to explore participants' perspectives while maintaining a structured focus on key themes. The interview guide was developed using the TOE framework and DOI theory to address technological, organizational, and environmental factors influencing adoption. Questions were designed to elicit insights into infrastructure readiness, employee attitudes, leadership commitment, and external pressures, reflecting the multi-faceted nature of analytics adoption.

Each interview was conducted virtually via Microsoft Teams, leveraging digital tools to accommodate participants' geographical dispersion and logistical constraints. The virtual format also provided a secure and convenient environment for participants, ensuring a higher response rate and engagement. Interviews lasted approximately 30–45 minutes, allowing sufficient time to explore participants' experiences and delve into emerging themes.

The semi-structured format allowed for probing and follow-up questions, enabling the researcher to uncover deeper insights into complex topics, such as the perceived compatibility of analytics tools with existing systems or the role of organizational culture in influencing adoption. For example, participants were asked, “How does your organization perceive the relative advantage of adopting retail analytics compared to current practices?” This question, rooted in the DOI theory, sought to explore how perceived benefits drive or hinder adoption decisions.

Interviews were audio-recorded with participants’ consent, transcribed verbatim, and coded using thematic analysis. Ethical considerations were emphasized throughout the process, with participants assured of confidentiality and anonymity. A pre-interview briefing outlined the study’s purpose and participants’ rights, fostering an open and transparent research environment (Bryman & Bell, 2015).

Rationale for Semi-Structured Interviews

Semi-structured interviews serve as the primary data collection method, providing a flexible yet focused approach to understanding participants’ experiences and perspectives[ref interview guid]. Unlike structured interviews that limit responses to predefined questions, semi-structured interviews allow participants to elaborate on their insights while enabling the researcher to probe emerging themes and clarify ambiguities. This adaptability is particularly valuable in exploring multifaceted topics like retail analytics adoption, where diverse factors—ranging from technological readiness to employee attitudes—contribute to decision-making (Saunders et al., 2019).

The interview protocol will be designed to explore themes such as the technological challenges of integrating retail analytics, organizational readiness for change, and the influence of external pressures like competition and regulations. For example, questions may investigate how leadership perceives the return on investment of analytics or how employees view the transition from manual to data-driven decision-making. This method ensures that the research captures both the technical and human dimensions of analytics adoption, providing a holistic understanding of the phenomenon. Additionally, the semi-structured format encourages participants to share context-specific anecdotes and insights that enrich the study’s findings.

3.2.3 Secondary Data Collection

To complement the primary data gathered through interviews, this study incorporated secondary data sources such as publicly available annual reports, industry analyses, and relevant policy documents. These materials provided macro-level insights into retail analytics adoption, supplementing the participant-generated findings with objective evidence of market trends, organisational performance, and strategic priorities (Saunders, Lewis, & Thornhill, 2019). For example, annual reports from the participating retail chains revealed historical technology investments and executive decision-making trajectories, while industry publications shed light on broader shifts in consumer expectations and persistent infrastructural challenges. Policy documents, including those relating to the Protection of Personal Information Act (POPIA), clarified the regulatory constraints encountered by traditional retailers managing sensitive customer data.

These secondary sources were thematically analysed using the same sensitising concepts derived from the Technology–Organisation–Environment (TOE) and Diffusion of Innovations (DOI) frameworks that guided the primary analysis. This allowed for triangulation across data types and enhanced the credibility of the findings. For instance, industry reports confirmed competitive pressures from e-commerce platforms mentioned by participants, while POPIA documentation substantiated the compliance hurdles discussed during interviews. Although the number of secondary sources was limited, their inclusion helped contextualise internal challenges—such as system integration issues or employee resistance—against broader market and legislative dynamics. This multi-dimensional approach contributed to a more robust and nuanced understanding of how systemic and individual-level factors jointly influence the adoption of analytics in South Africa's resource-constrained retail environment.

3.3 Data Analysis

The data analysis process in this study is designed to systematically interpret patterns and themes in the collected qualitative data, aligning with the theoretical underpinnings of the TOE framework and the DOI theory. Thematic analysis serves as the primary method, supported by NVivo software for efficient data organization and coding. Strategies such as triangulation, member checking, and maintaining an audit trail ensure the validity and reliability of the findings.

3.3.1 Thematic Analysis

Thematic analysis is employed to identify, analyse, and interpret recurring patterns (themes) within the data (Braun & Clarke, 2006). This approach is particularly suitable for qualitative research focused on understanding complex phenomena, such as the adoption of retail analytics in resource-constrained environments. By organizing data into meaningful categories, thematic analysis facilitates the exploration of both anticipated and emergent themes.

The analytical process integrates the TOE framework and DOI theory to guide the development of codes and themes. Deductive coding, informed by the TOE framework, categorizes data under key dimensions: technological, organizational, and environmental. For instance, codes may include "technological readiness," "leadership commitment," or "regulatory constraints," reflecting the factors identified in the framework (Tornatzky & Fleischer, 1990). Concurrently, inductive coding allows for themes to emerge directly from the data, capturing nuanced insights that may not fit predefined categories.

The DOI theory complements the TOE framework by offering a lens to explore the characteristics of innovation that influence adoption, such as relative advantage, compatibility, and complexity (Rogers, 1962). Themes related to the perceived benefits of analytics adoption, compatibility with existing systems, and resistance due to complexity are examined through the DOI perspective. For example, participants' descriptions of their decision-making processes might reveal how compatibility with legacy systems impacts their willingness to adopt retail analytics.

Thematic analysis progresses through iterative stages: familiarization with data, initial coding, theme identification, theme refinement, and theme naming. This structured process

ensures the analysis captures the depth and diversity of participants' experiences, providing a robust foundation for addressing the research objectives.

3.3.2 Use of NVivo Software

NVivo software supports the thematic analysis process by providing tools for efficient data organization, coding, and visualization. It enables the researcher to manage large volumes of qualitative data, including interview transcripts and secondary documents, within a centralized database (Bazeley & Jackson, 2013). Using NVivo, the researcher can code data systematically, categorize codes into themes, and visualize relationships between themes through matrix queries and thematic maps.

For this study, NVivo facilitates both inductive and deductive coding approaches. Deductive codes derived from the TOE framework and DOI theory are pre-established, while inductive codes are generated during the initial analysis phase. For example, NVivo allows the researcher to identify recurring phrases or concepts, such as "data-driven decision-making," which may emerge as an important theme under the organizational readiness dimension.

Additionally, NVivo's visualization tools enable the researcher to identify patterns across data sources, such as correlations between leadership perceptions and successful analytics adoption. This capability enhances the depth of the analysis and ensures that findings are supported by a rigorous, evidence-based process.

3.3.3 Validation of Findings

Ensuring the reliability and validity of the findings was paramount to this study, given its focus on understanding the adoption of retail analytics within South Africa's traditional retail sector. A triangulation strategy was adopted, enabling the integration of multiple data sources—interview responses, secondary documents such as annual reports and market analyses, and existing literature. This approach ensured consistency across insights while addressing potential biases. For example, participant accounts of regulatory challenges, particularly compliance with the Protection of Personal Information Act (POPIA), were cross-referenced with official policy documents and market reports to contextualize the perceived barriers and validate their impact on analytics adoption (Kshetri, 2021).

Member checking further contributed to the reliability of the findings by involving participants in the validation process. After preliminary themes were identified, participants were invited to review and confirm the interpretations, ensuring that their perspectives were accurately captured and reflected. This iterative feedback loop was especially critical in capturing sensitive organizational dynamics, such as leadership commitment to analytics adoption or employee resistance to technological change. By allowing participants to verify and refine the emerging themes, the study ensured a faithful representation of their lived experiences (Bryman & Bell, 2015).

The integration of the TOE framework and the DOI theory served as another layer of validation, enabling the analysis to balance systemic and innovation-specific considerations. For instance, while the TOE framework highlighted external pressures such as market competition and infrastructural challenges, the DOI theory provided insights into innovation attributes like relative advantage, compatibility, and observability. This theoretical triangulation illuminated the interplay between external and internal factors, such as how

regulatory compliance pressures (an environmental factor) intersect with the perceived complexity of analytics tools (an innovation-specific factor) to influence adoption decisions.

An audit trail was meticulously maintained to ensure transparency and replicability throughout the research process. Detailed records of coding decisions, thematic development, and NVivo outputs were systematically documented, allowing for a clear rationale behind analytical choices. For instance, emerging themes such as "data readiness" and "employee training gaps" were logged alongside direct quotations and references to secondary data, demonstrating how they aligned with or diverged from the TOE and DOI frameworks. This transparent approach not only enhanced the credibility of the findings but also provided a foundation for future research into similar contexts.

By employing these strategies, the study ensured a rigorous, systematic, and contextually grounded analysis of the factors influencing retail analytics adoption in South Africa's traditional retail sector. This methodological robustness supports actionable insights into overcoming the unique challenges faced by traditional retailers, contributing valuable knowledge to both academia and industry practice.

3.4 Ethical Considerations

Ethical considerations form a fundamental part of this research, ensuring that the study is conducted with integrity, transparency, and responsibility. Given the involvement of human participants, ethical principles such as informed consent, confidentiality, anonymity, and risk minimization were upheld in accordance with institutional and legal guidelines. The study adhered to the ethical guidelines set by the University of Cape Town's Ethics in Research Committee (see Appendix A for ethics approval) and complied with South African data protection regulations, including the Protection of Personal Information Act (POPIA) (2013), ensuring that participants' rights and data privacy were safeguarded.

Each stage of the research process, from participant recruitment to data analysis, was carefully designed to protect the well-being and privacy of participants. Ethical approval was obtained prior to data collection, and strict confidentiality protocols were followed throughout the study. Participants were fully informed of their rights and provided with a formal consent form detailing the study's purpose, methodology, and data protection measures (see Appendix B for consent form). Additionally, mechanisms were put in place to allow participants to withdraw their participation at any stage without any repercussions. To further enhance transparency and reciprocity, participants were also informed that they would receive a summary of the study's key findings upon completion.

The following subsections provide a detailed discussion of the ethical approval process, informed consent procedures, confidentiality safeguards, and measures taken to minimize potential risks to participants.

3.4.1 Ethical Approval

Before commencing data collection, ethical clearance was sought and obtained from the University of Cape Town's Ethics in Research Committee, which rigorously evaluated the study's research design, objectives, and methodology. The approval process required a comprehensive ethics application, detailing the research questions, participant selection criteria, data collection procedures, and ethical safeguards implemented to ensure participant

autonomy, confidentiality, and data security. The committee's review process also assessed potential ethical risks, ensuring that the study met both institutional and national ethical standards.

The approval process specifically examined the informed consent procedures, data management policies, and potential risks associated with participant disclosure. Ethical clearance was granted on the basis that all necessary precautionary measures were in place to protect participants' rights and welfare. All interactions with participants adhered strictly to the ethical guidelines outlined in the approval letter, ensuring that the research was conducted with academic integrity and ethical responsibility.

Additionally, compliance with POPIA was a key consideration, given that the study involved collecting sensitive business insights related to analytics adoption within South African retail organizations. The ethical approval committee required the research design to include stringent data protection protocols, ensuring that participant confidentiality was maintained throughout the study. The next section outlines how these ethical principles were operationalized in the study's informed consent procedures.

3.4.2 Informed Consent

A comprehensive informed consent process was implemented to ensure that all participants fully understood their rights, the study's objectives, and the procedures involved prior to voluntarily agreeing to take part. Before participation, each individual received a detailed consent form outlining the purpose of the study—namely, its significance within the context of retail analytics adoption in South Africa—and clarifying the nature of their participation, including data collection methods and the expected time commitment. The form also explained confidentiality and data protection measures, guaranteeing anonymity of personal and professional identities; stated participants' right to withdraw at any time without providing justification or facing negative consequences; and specified that audio recordings and transcriptions would be used solely for research purposes, with explicit participant consent required for such recordings.

In addition, the form described how data storage and security procedures would adhere to POPIA (2013) regulations, ensuring full compliance with legal obligations. To reinforce understanding and prevent any sense of coercion, participants were given a verbal briefing in which they could ask questions and seek clarification before signing the consent form (Bryman & Bell, 2015). For virtual interviews conducted via Microsoft Teams, a digital process was followed: participants received the form electronically and submitted written email confirmation of consent prior to the interview. This approach maintained the same ethical rigor as in-person sessions. The following section describes the specific confidentiality and data protection measures undertaken to safeguard participant privacy throughout the study.

3.4.3 Confidentiality and Anonymity

Strict confidentiality and anonymity protocols were applied throughout this research to safeguard participant privacy, especially in light of the study's commercially sensitive subject matter. Participants and their organizations were protected by assigning pseudonyms and removing any identifiable information (such as company names or specific job titles) from the research findings, ensuring that interview statements were attributed only to broad role

categories (e.g., “Retail Executive,” “IT Leader”). All audio recordings and transcriptions were stored on encrypted, password-protected servers, in accordance with POPIA (2013) data-protection guidelines. Access to raw interview data was restricted to the principal researcher and authorized supervisors, further reducing the risk of data breaches or unauthorized viewing.

In alignment with the ethics approval letter (Ref: Ethics Approval Letter), the data retention policy stipulates that interview materials will be held securely for five years before being permanently deleted. These measures were clearly communicated to participants at the outset, ensuring that they were fully informed and confident in the study’s privacy safeguards. The subsequent section discusses the steps taken to minimize risks and uphold participant welfare over the course of the research.

3.4.4 Minimizing Risks

While this study posed no physical risks, it acknowledged the potential psychological or professional risks of discussing business practices and technology adoption in retail organizations. To address these concerns, several precautions were adopted.

First, interview questions were designed with question sensitivity in mind, avoiding controversial or highly sensitive matters (Saunders, Lewis, & Thornhill, 2019). Second, participants were reminded that their participation was entirely voluntary, with the right to withdraw at any point or skip any question if they felt uneasy. Third, the decision to conduct interviews via Microsoft Teams offered greater convenience and privacy, creating a more relaxed environment than might be experienced in face-to-face settings.

Finally, a post-interview debriefing and summary allowed participants to understand how their contributions informed the study’s broader insights, thus reinforcing trust and fostering a sense of reciprocity. Together, these measures upheld the ethical principles of autonomy, beneficence, and justice, ensuring that all participant involvement remained voluntary, respectful, and free from harm (Creswell & Creswell, 2018).

3.5 Limitations of the Methodology

3.5.1 Scope of Findings

The qualitative case study design prioritizes depth and contextual richness over breadth, focusing on specific cases rather than a broad cross-section of the population. While this approach allows for an in-depth understanding of the factors influencing retail analytics adoption within selected traditional retail chains, it inherently limits the generalizability of the findings (Yin, 2018). Insights derived from this study are specific to the participants and organizations involved and may not fully capture the diversity of experiences across the entire South African retail sector or in other developing economies. Future research employing quantitative methods or larger samples could complement this study by enhancing generalizability.

3.5.2 Subjectivity and Potential Biases in Interviews

Semi-structured interviews, while valuable for eliciting rich, detailed data, rely on participants' subjective accounts. This reliance introduces potential biases, such as recall bias, where participants may inadvertently misremember events, or social desirability bias, where they may provide responses they believe are expected or favourable rather than entirely truthful (Bryman & Bell, 2015). These biases could affect the accuracy and reliability of the data, particularly when discussing sensitive topics such as organizational challenges or leadership decisions. To mitigate these issues, the researcher employed strategies such as triangulating interview data with secondary sources and conducting member checking to verify participants' responses.

3.5.3 Variability in Secondary Data Reliability

Secondary data, including annual reports, market analyses, and policy documents, was used to complement interview findings and provide contextual insights. However, the reliability and relevance of secondary data may vary, particularly when such documents are created for purposes other than academic research. For instance, annual reports may emphasize favourable outcomes while omitting challenges or failures, potentially skewing the analysis. Additionally, some secondary data sources may not directly align with the specific context of retail analytics adoption in South Africa, necessitating careful interpretation and validation against primary data (Saunders, Lewis, & Thornhill, 2019).

3.5.4 Time Constraints and Logistical Challenges

Time constraints posed significant challenges during the data collection phase, particularly in scheduling interviews with participants holding senior positions in traditional retail chains. Their demanding roles often resulted in delays or limited availability for extended discussions. Additionally, the virtual nature of interviews required participants to have access to a working laptop, a stable internet connection, and Microsoft Teams. These prerequisites, while necessary for remote data collection, may have excluded potential participants without access to such resources, introducing a potential bias in the sample.

Furthermore, the virtual format, while practical, limited the ability to observe non-verbal cues and the contextual environment of participants, which could have provided additional insights. Although efforts were made to create a comfortable and secure interview setting, such limitations highlight the trade-offs inherent in using virtual methods for qualitative research.

Chapter 4: Findings

4.1 Introduction

This chapter presents the findings of a qualitative case study on the adoption of retail analytics in South Africa's traditional retail sector. Drawing on 15 semi-structured interviews, the investigation employs both the Technology–Organisation–Environment (TOE) framework (Tornatzky & Fleischer, 1990) and Rogers' (2003) Diffusion of Innovations (DOI) theory to explore how retail analytics solutions are introduced, implemented, and expanded in a market characterised by infrastructural limitations, diverse consumer profiles, and competitive pressures.

The study participants represented a diverse range of roles and expertise, spanning executive leadership, IT infrastructure, data science, operations management, sustainability, and marketing analytics. Table 4.1 provides a detailed breakdown of the respondents' roles, key focus areas, and the size of their organisations, ensuring a comprehensive perspective on how analytics adoption unfolds across various business functions. This respondent distribution offers insights into both high-level strategic decision-making and operational implementation challenges, allowing for a nuanced exploration of how different stakeholders perceive and navigate analytics adoption.
The overarching research aim, introduced in Chapter 1, was to uncover the drivers and barriers influencing the uptake of advanced analytical tools in a predominantly brick-and-mortar retail context. To achieve this aim, three broad research objectives were pursued. From a technological perspective, the study sought to identify and analyse key technological factors—such as infrastructure, integration, data management, and security—that enable or constrain the adoption of retail analytics. From an organisational perspective, the focus was on examining how corporate culture, organisational structure, leadership dynamics, and human resource capabilities influence the willingness and readiness of businesses to incorporate analytics into their daily operations. Lastly, from an environmental perspective, the research assessed external elements, including regulatory mandates, market competition, and socio-cultural factors, to understand how these influences shape the speed and manner in which retail analytics diffuses across organisations.

Guided by these objectives, this chapter is structured around the core components of the TOE framework, enriched with insights from DOI theory. Section 4.2 focuses on the Technological dimension, examining infrastructural readiness, system integration challenges, tool complexity, and data security. Section 4.3 moves on to Organisational themes, including culture, workforce data literacy, decision-making hierarchies, and resistance. Section 4.4 addresses Environmental forces, such as budgetary constraints, regulations, competitive pressures, cultural nuances, and emerging concerns around sustainability. Finally, Section 4.5 integrates these findings with the five attributes of DOI—relative advantage, compatibility, complexity, trialability, and observability—providing a nuanced picture of how retail analytics innovations diffuse within South African traditional retail.

Throughout this chapter, direct quotes from participants (e.g., "R1 stated…") vividly illustrate the study's qualitative data. Each individual holds distinct roles—executive managers, data scientists, systems architects, middle managers, and frontline supervisors—offering a multi-layered view of retail analytics adoption. The respondent breakdown in Table 4.1 below ensures that perspectives from different organisational levels are incorporated, capturing both strategic imperatives and operational realities. The findings collectively emphasise that while retailers increasingly recognise the potential of data-driven decision-making to optimise inventory, reduce costs, and enhance customer experiences, they face intertwined technological, organisational, and environmental obstacles. By systematically applying both TOE and DOI frameworks, this chapter illuminates the interplay among legacy infrastructures, cultural mindsets, regulatory realities, and strategic imperatives, thus setting the stage for the discussion and recommendations in Chapter 5.

RESPONDENT ID	ROLE/POSITION	KEY EXPERTISE/FOCUS	ORGANIZATION SIZE
R1	IT Director	Technological infrastructure, change management, data privacy, and security	Large organization
R2	Operations Manager	Workforce capability, decision-making hierarchy, system integration challenges	Large organization
R3	CEO	Strategic decision-making, financial investments, driving cultural shift toward analytics	Large organization
R4	Data Scientist	Data integration, machine learning applications, real-time analytics, and data security	Large organization
R5	Executive Leadership	Strategic vision, regulatory compliance, data-driven decision-making culture	Large organization
R6	Data Analyst	Consumer behavior analysis, sustainability, predictive and prescriptive analytics	Medium-sized organization
R7	Senior Data Analyst	Consumer behavior insights, data visualization, predictive modeling	Medium-sized organization
R8	Systems Architect	Integration challenges, systems compatibility, regulatory compliance	Medium-sized organization
R9	Executive	Regional analysis, operational efficiency, localized strategies	Medium-sized organization
R10	Marketing Director	Targeted marketing, campaign performance, ROI analysis	Medium-sized organization
R11	Data Engineer	Data pipeline optimization, integration, governance	Large organization
R12	Sustainability Officer	Environmental sustainability, energy optimization, and supply chain management	Large organization
R13	Chief Data Officer (CDO)	Data governance, compliance, strategic data initiatives	Large organization
R14	Financial Analyst	Budgeting, ROI analysis, financial prioritization	Large organization
R15	Customer Insights Manager	Consumer behavior, loyalty program analysis, segmentation	Large organization

Table 4.1: *Respondent Details*

4.2 Technological Dimension

Under the TOE framework, the technological dimension encompasses how internal IT systems, existing platforms, data management practices, and perceived tool complexity shape the adoption of new technologies. The interview data yielded four significant sub-themes: Infrastructure Readiness, Integration Challenges, Complexity of Tools, and Data Security & Privacy. Each is discussed in turn, with insights contextualised by the roles and perspectives of the respondents.

4.2.1 Infrastructure Readiness

Legacy systems and inconsistent infrastructure remain critical challenges in adopting retail analytics. Many South African retailers operate with hardware and software that are decades old, primarily due to the high cost of replacement and logistical challenges in rural areas. As R14 emphasised, *"Our stores operate on various point-of-sale systems—some are quite old—and we do not have a standardised way to capture or transfer data."* Focusing on financial prioritisation, R14's perspective underscores the resource constraints faced by smaller organisations, where the upfront capital needed to replace obsolete systems can stall real-time analytics implementation (Davenport & Harris, 2017).

From a broader perspective, R1 in a large organisation pointed to the sheer scale of siloed infrastructures, stating that *"Our organisation is grappling with integrating modern tools into legacy systems that are spread across multiple silos."* Such fragmentation aligns with Randhawa's (2019) findings that legacy infrastructure limits scalability and hinders seamless integration with analytics tools. Internet connectivity represents another persistent bottleneck, particularly in rural areas with intermittent bandwidth. R8 noted, *"Some areas still have patchy or slow internet, making real-time analytics nearly impossible."*
Bradlow et al. (2017) corroborate this, showing how inadequate internet infrastructure delays data capture and processing, impeding timely decision-making. Yet, research suggests that cloud-based solutions are increasingly being explored as a workaround for these infrastructure limitations. In transitioning to a centralised, cloud-based storage model, organisations can offload intensive computing tasks from local servers to more robust remote environments, thereby partially mitigating bandwidth constraints (Gupta et al., 2020).
R15 highlighted the cultural and operational hesitation inherent in this shift, explaining that *"We have begun migrating parts of our data to a centralised, cloud-based storage solution, but leadership remains cautious about security, costs, and how quickly staff can adapt."* This tension between recognised benefits—such as streamlined data consolidation and potential cost savings—and apprehension over data governance and operational disruptions remains a recurring theme in retail analytics adoption.

Respondent 7 offered a unique viewpoint, particularly on balancing legacy systems with new technologies, stating that *"We see cloud migration as a long-term strategy. However, for day-to-day operations, we've started using mobile analytics apps to track sales in real time. This hybrid approach lets us bypass some infrastructure constraints without overhauling everything at once."* R7's perspective underscores the incremental approach many retailers are taking, where mobile analytics serve as an intermediary tool before full-scale cloud adoption.

Indeed, mobile analytics tools have shown considerable promise: retailers adopting these reported an 18% improvement in sales tracking efficiency compared to those relying solely on static, desktop-based systems. While the broader retail analytics space has been widely studied, literature specifically addressing mobile analytics within the adoption phase remains limited. Such tools often fall under the umbrella of broader "big data" or "analytics" discussions, leaving a gap in understanding how handheld devices and real-time interfaces impact user engagement, data accuracy, and decision-making speed in resource-constrained environments.

R7 elaborated on this gap, stating that *"Most studies I've encountered talk about advanced analytics in general, but very few dive into how mobile platforms actually help bridge day-to-day challenges, especially in stores with poor internet or outdated systems."* This observation reflects the nascent state of empirical research on mobile-specific adoption challenges in

traditional retail contexts. Nevertheless, the evidence so far indicates that mobile solutions can alleviate some of the immediate barriers posed by older IT infrastructure and inconsistent connectivity (Masuku & Zubane, 2022). As R7 and others noted, however, these tools must be supported by robust data governance, adequate training, and long-term cloud migration plans to ensure sustainability and scalability.

While infrastructure constraints remain a significant barrier, retailers are finding incremental solutions through mobile analytics and phased cloud migration. However, a major hurdle that persists even with improved infrastructure is the challenge of system integration, as different platforms often remain incompatible. The next section explores the complexities retailers face in ensuring seamless interoperability between legacy and modern systems. This strategy aligns with the broader assertion that significant upfront investment in training and change management is critical for realising the full benefits of retail analytics across varying infrastructural contexts (Gupta et al., 2020).

4.2.2 Integration Challenges

Even when IT infrastructure is moderately robust, integrating disparate systems emerged as a significant stumbling block. Mergers, expansions, or departmental autonomy often result in multiple, non-interoperable software applications. For example, R2 noted that *"One of our biggest challenges stems from legacy platforms that require a lot of customisation before they can interface with modern analytics software. People want immediate results but are hesitant to invest the time in system integration and testing."* This feedback highlights the practical frustrations faced by managers overseeing daily operations, balancing short-term results and long-term investments.

Similarly, R12 (Sustainability Officer) described the labour-intensive nature of integration, stating that *"We had to write multiple scripts just to pull inventory data from a few store systems. Every new integration becomes a custom project, which can quickly lead to budget overruns."* As someone focused on environmental sustainability and supply chain optimisation, this perspective highlights how resource constraints directly impact analytics implementation.

Integration issues often stem from inconsistent data labelling across departments. R4 (Data Scientist) highlighted that *"Units sold might mean net units after returns for one team, while another team still includes returns in their final tally. That difference throws our entire forecasting model off."* This finding reflects the disconnect between technical teams and operational staff, emphasising the need for robust data governance.

These challenges underscore the necessity of organization-wide data standardization policies, such as master data management (MDM) frameworks, to ensure stable and scalable analytics deployments (Mikalef et al., 2020). MDM provides a unified and consistent view of critical business entities, facilitating improved decision-making and operational efficiency. However, implementing MDM frameworks can be complex, often encountering organizational, technical, regulatory, and cultural obstacles. For instance, organizations may face resistance to change, data silos, and a lack of clear data ownership, all of which can impede the successful adoption of MDM practices (Davis & Albright, 2021).

R5 added a strategic perspective, noting that *"Our organization is slowly adopting data governance frameworks, but implementation is inconsistent across regions."* This comment

from a senior leader highlights the strategic importance of alignment in ensuring integration success. Inconsistent implementation of data governance frameworks can lead to fragmented data practices, undermining the effectiveness of analytics initiatives. To address these challenges, organizations are increasingly adopting data governance as a means to ensure that the quality of data entering their systems remains sufficient, thereby enhancing trust in decision-making processes (Wang & Strong, 2022).

4.2.3 Complexity of Tools

The complexity of analytics platforms emerged as a consistent concern, reflecting the divide between technically adept staff and other organisational roles. Data scientists and technically proficient employees, such as R4, often embrace advanced features like machine learning algorithms, predictive modelling, and real-time dashboards. In contrast, store managers and mid-level executives, such as R2, frequently perceive these tools as intimidating or excessively time-consuming to learn.
R10 emphasised the importance of designing platforms with varying levels of engagement, stating that *"If a platform's learning curve is too steep, we risk low adoption. We typically look for solutions that have multiple user 'levels' of engagement—like a beginner dashboard for daily use and an advanced interface for data specialists."*

Similarly, R2 noted the dual-edged nature of complexity, explaining that *"Robust tools can provide powerful insights—like real-time stock replenishment recommendations. On the other hand, if it is not intuitive or if training is lacking, employees revert to traditional methods."*
To address these challenges, many organisations have adopted multi-layered analytics solutions. Simplified dashboards tailored for everyday operations—such as monitoring daily sales and stock levels—coexist with specialised environments for data scientists like R4, who conduct advanced analyses.

However, respondents emphasised the critical role of training and vendor support. R15 observed that *"Without consistent training and vendor support, even powerful tools become redundant. Teams often fall back on older, manual methods despite having access to advanced solutions."* Research by Gupta et al. (2020) corroborates these findings, emphasising that robust training programmes and adaptive learning environments enhance adoption rates and maximise returns on technology investments.
The narrative of complexity extends beyond usability to broader organisational implications. R9 pointed out that *"Overly complex tools can create friction between departments, particularly when data outputs are inconsistently interpreted."* This highlights the importance of organisation-wide data governance standards and cross-functional communication (Davis, 1989).

4.2.4 Data Security & Privacy

Given the sensitive nature of retail transactions and personal consumer information, participants universally cited compliance with the Protection of Personal Information Act (POPIA) and other relevant regulations as critical considerations. R1 remarked that *"Data security and privacy are always top-of-mind for any organisation, particularly in retail. A data breach would have devastating consequences—not just from a regulatory standpoint but also in terms of consumer trust."*

Similarly, R14 described specific measures, stating that *"I frequently anonymise or pseudonymise datasets before applying machine learning techniques. We also have strict access controls—only specific personnel can view sensitive fields."*
While these measures are essential for compliance and ethical practices, they add layers of complexity to data pipelines. R8 explained that *"Extensive privacy protocols often limit data utility for advanced analytics. For example, anonymised data might prevent us from identifying specific trends or patterns critical to business insights."*
Gupta et al. (2020) emphasise that achieving this balance often requires innovative solutions like differential privacy or federated learning, which minimise risks without compromising analytical accuracy.
Smaller retailers face unique challenges in this area. As R12 noted, *"For larger enterprises, compliance standards are embedded into their systems. Smaller businesses, however, struggle to implement the same level of security due to limited resources."*

4.2.5 Store Cards and Automated Storefronts

A recurring theme in the interviews was the limited return on investment (ROI) sometimes associated with loyalty or store cards, as well as the technical complexity and data demands of automated store concepts (e.g., Amazon Go–style smart stores). While loyalty cards offer valuable consumer data, respondents expressed concern that this information is often underutilised. R11 noted that *"We offer these cards for free to gather insights, but the data isn't always analysed effectively. Tourists, for example, sign up and leave, so we lose the continuity that makes analytics valuable."*

Other respondents emphasised that not all shoppers consistently carry or use their loyalty cards, undermining data capture efforts. R7 highlighted that *"We're collecting reams of transactional info, but many large retailers barely scratch the surface in terms of analytics. The cost of the loyalty programme outweighs any ROI if they don't capitalise on the insights."*

In contrast, automated storefronts promise frictionless shopping experiences and richer, more granular data through advanced sensors and cameras. Yet, the technological barriers can be significant. R7 further elaborated that *"Setting up a store like Amazon Go requires dozens of high-resolution cameras that capture every movement. You then need to store, analyse, and secure that video data—an entire technology stack that doesn't come cheap."*

From an analytics standpoint, these systems often rely on image recognition and other niche technologies that demand specialised skill sets. As Gupta et al. (2020) suggest, integrating machine learning with video analytics adds complexity—especially for retailers still grappling with legacy infrastructure. As a result, for many organisations, the cost and expertise required to implement such systems can outweigh immediate benefits.

4.3 Organizational Dimension

The organisational dimension explores how internal structures, cultures, human resources, and leadership attitudes shape or impede technology adoption (Tornatzky & Fleischer, 1990). Four main sub-themes surfaced from the interview data: (a) Culture & Structure, (b)

Workforce Capability & Data Literacy, (c) Decision-Making & Hierarchy, and (d) Employee Resistance.

4.3.1 Organisational Structure & Decision-Making

Interviewees frequently depicted their organisations as hierarchical, with executive committees or boards setting strategic directions, which are then passed down to mid-level managers for execution. According to R2 (Operations Manager), *"Historically, decisions have been made at the executive level with limited input from mid-level managers. However, we are seeing a shift, where analytics teams are increasingly involved in strategy discussions."* While top-level endorsement can rapidly move analytics projects forward—especially if executives champion a specific initiative like inventory optimization—it can also hinder innovation if priorities shift or if the leadership team is uncertain.

R2 highlighted the dual nature of hierarchical structures, explaining that *"When the executive committee champions a specific analytics project—like optimising stock procurement—it moves forward rapidly. Conversely, if there is uncertainty at the top, projects can stall for months. "*Similarly, R15 described reorganizing her firm to establish a central Data Science Department as a means of reducing siloed decision-making, stating that *"After joining, I pushed to establish a Data Science Department as a central hub, encouraging cross-functional collaboration. Rather than each department running analytics in isolation, we now have a more unified structure."* Yet, organisational silos persist. Some department leaders fear that analytics might expose inefficiencies, leading to reluctance in data sharing.

R9 noted that *"We have a strong executive committee, but each functional department interprets their directives a bit differently. So, bridging these silos often requires day-to-day relationship building, not just memos from the top."*

In many cases, short-term ROI dominates the executive mindset. R14 explained how incremental proofs of concept are used to gain leadership support, highlighting that *"If senior leadership does not see immediate ROI, approvals get stuck. We have found that small proofs of concept help push things along—demonstrating tangible gains in one product line or store."* This strategy aligns with Rogers' (2003) concept of Trialability, indicating that pilot projects can reduce uncertainty and secure buy-in for broader adoption. Over time, as these smaller victories accumulate, executives become more comfortable allocating resources to larger, more transformative analytics initiatives (Randhawa, 2019).

4.3.2 Data-Driven Culture

Beyond hierarchical structures, a growing data-driven culture underpins many successful analytics rollouts in traditional retail. Respondent 11 provided quantitative insights into how certain organizational practices can accelerate analytics adoption, stating that *"In our benchmarking, retailers with a dedicated analytics team were 40% more likely to integrate data-driven decision-making across multiple departments. Investment in employee training led to a 25% improvement in analytics tool adoption rates, ensuring that end-users feel confident in interpreting and acting on data."* These findings underscore the value of specialized analytics roles—not only to execute technical tasks but also to advocate for data-centric decision-making across the organization. Coupled with robust training, a dedicated

analytics function can address skill gaps and foster a cultural shift toward evidence-based practices.

R11 also highlighted the importance of incentivizing data-driven decisions as a catalyst for cultural change, explaining that *"Retailers that tied bonuses or recognition to data-backed insights saw a noticeable boost in overall productivity. Employees become more proactive in finding patterns and trends when their performance metrics include data usage."* Such incentive mechanisms unite different levels of the hierarchy around a common goal. Rather than relying solely on top-down mandates, these programs encourage frontline employees and mid-level managers to experiment with analytical tools and share success stories. This is especially important in large, traditional retailers where departmental silos can undermine cross-functional initiatives.

When top-down direction converges with bottom-up empowerment, organisations are more likely to embed analytics sustainably. As R2 explained, *"a growing middle layer of data-savvy managers often becomes the linchpin that translates executive priorities into day-to-day actions."* Meanwhile, centralised analytics teams—like the one R15 helped create—provide consistent methodologies, ensure data quality, and offer ongoing support to various business units.
By combining clear executive sponsorship, dedicated analytics personnel, and reward systems that acknowledge successful data-driven projects, retailers can mitigate resistance and gradually align the entire hierarchy around analytics. Pilot projects (a demonstration of Trialability) further minimize risk by showcasing tangible benefits in a controlled setting—thus building momentum for broader rollouts.

4.3.3 Workforce Capability & Data Literacy

Another vital organisational factor influencing retail analytics adoption is the workforce's capacity to utilise analytics effectively. Respondents consistently depicted a broad spectrum of data literacy across different roles and departments. R2 contrasted e-commerce and traditional store teams, stating that *"Teams in e-commerce are comfortable with metrics and A/B testing, while store managers might still do inventory counts by hand."* This gap underscores the uneven distribution of analytics skills, where frontline employees may lag in basic data competencies while digital or headquarters-based teams readily engage with complex metrics.

Many retailers attempt to bridge these disparities through structured training programmes. As R4 detailed, *"We introduced 'data essentials' workshops for all employees, explaining basic KPIs. For more advanced roles, we offer workshops on data visualisation tools or predictive analytics. We also sponsor certifications for those who want to dive deeper."* Despite these initiatives, time constraints and high staff turnover can disrupt learning continuity. R14 emphasised that *"We do lunch-and-learn sessions, but when staff rotate or leave, we lose that knowledge."* Such challenges highlight the need for sustained, institutionalised training efforts—rather than one-off sessions—to maintain momentum. Gupta et al. (2020) corroborate this view, arguing that continuous training and mentorship programmes result in higher adoption rates and sustained performance improvements.

Respondent 7 expanded on innovative approaches to upskilling employees, noting that *"We've partnered with a local university to offer a certificate programme tailored for retail analytics. This collaboration not only raised our employees' skill levels but also validated*

their efforts, which in turn increased analytics adoption by roughly 30%." Such partnerships provide structured curricula, expert instructors, and hands-on projects—factors that align well with the demands of fast-paced retail environments. According to R7, these programmes also foster cross-functional peer learning, as employees from different regions and departments collaborate on real-world case studies.

Respondent 11 further highlighted the role of incentive structures in driving engagement with training resources and analytical tools, explaining that *"We introduced monthly challenges where teams showcase how they've applied analytics to solve store-level problems. This incentivising of data-driven strategies led to about a 20% increase in our employees actually using dashboards and insights."* R11's observation underscores the importance of recognition and rewards—whether monetary bonuses or public accolades—for employees who actively employ analytics in their decision-making. By tying performance metrics to data usage, retailers not only encourage staff to develop data literacy but also embed a culture of continuous improvement (Davis, 1989).

4.3.5 Cultural Resistance

Staff resistance emerged as a significant barrier to analytics adoption, often driven by fears of job displacement, concerns over increased performance monitoring, and a lack of familiarity with new technologies. Employees, particularly managers, expressed apprehension that analytics-driven decision-making might reduce their influence or expose underperformance. Respondent 6 (Data Analyst) noted that *"Some managers worry that algorithms might make their roles less important or that analytics might highlight underperformance… So they either resist it or only use it superficially."* As a Data Analyst, Respondent 6 has firsthand experience observing how analytics outputs can challenge existing workflows, contributing to managerial resistance. Similarly, Respondent 2 described resistance manifesting as skepticism, stating that *"We've operated fine for years, so why disrupt a proven method?"* This insight from a senior leader emphasizes how resistance can stem from entrenched cultural attitudes and organizational inertia, particularly when analytics threatens established norms.

Resistance is also heightened when employees fear that analytics tools will be used to scrutinize performance unfairly, leading to defensive attitudes and reluctance to engage with data-driven decision-making. To address these challenges, organizations have employed structured change management frameworks, such as Kotter's (1996) model, which emphasizes coalition-building, short-term wins, and sustained momentum. Respondent 1 (IT Director) underscored the importance of leadership in driving change, explaining that *"Fostering a willingness to change—an appetite for adopting new processes and tools—alongside programs to facilitate these transitions."* As an IT Director, Respondent 1's perspective highlights the technical and cultural groundwork required to promote analytics adoption. Participatory design, where employees help define data collection parameters and metrics, has been used to foster a sense of ownership and reduce apprehensions. Additionally, some organizations have implemented incentive-based analytics adoption programs to encourage engagement.

Respondent 15 shared a practical approach, stating that *"We involve staff early in the process, showing them how analytics can make their jobs easier, like automating repetitive tasks. That helps ease their fears."* This perspective underscores the importance of demonstrating immediate, tangible benefits to build trust and reduce resistance. Transformational leadership,

characterized by clear vision and effective communication, plays a pivotal role in shaping a culture that is open to analytics-driven change, as supported by Mikalef et al. (2020). Despite these efforts, resistance varies significantly across roles and departments. Respondent 9 (Executive) observed that *"Analytics adoption is easier in data-heavy functions like marketing but much harder in store operations, where traditional methods dominate."* This highlights the need for tailored strategies that address role-specific concerns. Store managers and mid-level employees, for example, often revert to traditional methods due to a lack of confidence in analytics tools. Ensuring that training programs account for different technical backgrounds and use cases is essential for reducing resistance.

These findings align with Rogers' (2003) Diffusion of Innovation Theory, which stresses the importance of Compatibility (aligning new technology with existing workflows) and Trialability (allowing staff to experiment with analytics in a low-risk setting) to overcome cultural resistance. Ultimately, the interplay between leadership style, organizational culture, and resistance dynamics remains a critical area for further exploration. Addressing these factors can provide a more nuanced understanding of how organizations navigate resistance and foster a culture of openness to analytics-driven change. By leveraging these insights, organizations can design holistic strategies to ensure analytics adoption aligns with broader cultural transformation.

4.4 Environmental Dimension

The external environment encompasses a range of factors that significantly influence the adoption of advanced analytical tools, including financial and budgetary constraints, regulatory and compliance mandates, competitive pressures, cultural and societal factors, and sustainability and environmental initiatives (Tornatzky & Fleischer, 1990). These elements shape how organizations prioritize and implement analytics solutions, often requiring them to navigate complex trade-offs between regulatory adherence and competitive positioning.

4.4.1 Financial & Budgetary Constraints

Financial considerations play a pivotal role in shaping analytics adoption, particularly in traditional retail environments characterized by tight profit margins and competing capital demands. Respondents frequently emphasized the need for cost-effective strategies. Respondent 12 remarked that *"We're forced to be very selective, often opting for low-cost or open-source solutions. Even then, the budget gets scrutinized closely, which slows or narrows the scope of analytics."* This insight reflects the dual pressures faced by sustainability-focused leaders, who must balance cost containment with broader corporate objectives, such as reducing environmental impact or improving supply chain efficiency.
Respondent 15 explained a phased approach, stating that *"We adopt a phased approach: start small, demonstrate ROI, then expand gradually. That's the only way to convince leadership analytics is worth ongoing investment."* As a manager focused on consumer behavior and loyalty programs, Respondent 15 underscores the importance of demonstrating tangible, immediate benefits to secure buy-in for long-term analytics investments. This strategy aligns with literature by Gupta et al. (2020), which highlights that while phased approaches minimize risk, they may also limit innovation by prioritizing short-term returns over transformative initiatives.
The tension between incremental progress and the need for transformative innovation is particularly acute for smaller retailers. Respondent 3 noted that *"We can't afford to make large-scale investments without clear results. Phased implementations allow us to build*

confidence with leadership while avoiding financial risks." This strategic perspective highlights how CEOs must weigh analytics adoption against broader financial priorities, ensuring projects align with organizational goals without overextending resources.
The reliance on low-cost or open-source solutions further illustrates the trade-offs between cost savings and scalability. While these tools provide an accessible entry point, they may lack the robustness required for high-impact initiatives, such as AI-driven recommendation engines or real-time pricing models. Linking these financial dynamics to the TOE framework could provide a structured understanding of how financial constraints interact with organizational readiness and environmental pressures to shape analytics adoption strategies.

4.4.2 Rolling Out Automated Solutions

While automated storefronts and advanced analytics platforms present opportunities for improved efficiency and unique customer experiences, respondents underscored the environmental realities and socio-economic constraints that can impede broad deployment—particularly in the South African retail context. As R3 (CEO) explained:
"We lease most of our buildings, so implementing major changes like camera arrays or sensor gates is a lengthy approval process. By the time we get the green light, we need to revisit the board for additional funding, and it becomes a tough sell."

High crime rates also introduce challenges to fully automated models. R11) observed:
"You can't simply replicate the Amazon Go concept in areas with high theft risk. We need human oversight, so the argument that automation is cheaper doesn't always hold up here."
Moreover, South Africa's high unemployment rate makes the notion of technology replacing human workers a sensitive issue. Respondent 7 (Digital Transformation Lead) noted:
"The board is wary of rolling out fully automated stores at scale because it could be perceived as cutting jobs. That's not a great message, especially in communities with high unemployment."

As a practical compromise, several participants suggested testing automated technologies in select, high-traffic stores or "flagship" locations that can better absorb the upfront costs. Even so, convincing stakeholders requires robust cost-benefit analyses to ensure that the investment aligns with broader organisational goals and societal expectations. Research corroborates that in resource-constrained or high-crime markets, incremental pilots are often preferred over sweeping, chain-wide transformations (Gupta et al., 2020).

Consequently, while advanced concepts like Amazon Go have garnered global attention, many South African retailers adopt a cautious approach. Respondent 3 concluded:
"We might deploy these innovations in our top 10 performing stores—where footfall is high and the environment is more controlled. But rolling them out nationwide won't be feasible until the economic and infrastructural conditions improve."

This prudent, phased strategy aligns with the wider theme that environmental pressures—such as leasing constraints, local crime rates, and socio-economic imperatives—often supersede pure technological readiness when retailers evaluate whether or how to deploy automation.

4.4.4 Regulatory & Compliance

Regulatory imperatives, particularly compliance with the Protection of Personal Information Act (POPIA), emerged as a critical factor influencing analytics adoption in South Africa's retail sector. Retailers must navigate extensive consumer data—ranging from purchase histories and demographic profiles to location-based information—while mitigating risks such as legal penalties, reputational damage, and erosion of consumer trust.
Respondent 1 (IT Director) underscored the technical and operational responsibilities that accompany strict adherence to regulations, stating that *"We adhere to regulations, seeking explicit consent from customers and storing only the data we need. Additionally, access control is crucial: only relevant personnel can view sensitive information."*

In a similar vein, Respondent 14 highlighted the procedural complexities of compliance, explaining that *"Under POPIA, we have to ensure each dataset we analyse complies with the scope of consent. That means anonymizing sensitive fields and reviewing how data flows from collection to modelling."* Such measures reinforce data ethics and consumer privacy but can also slow analytics workflows by imposing additional layers of review and governance.

Smaller retailers, in particular, face resource constraints that make these standards harder to meet. Respondent 3 remarked that *"Larger companies have dedicated teams for compliance, but we often have to rely on external consultants, which adds costs and delays."* Respondent 7 elaborated on how formal data protection compliance programs can bolster retailer credibility and reduce legal exposure, stating that *"We instituted mandatory compliance training across all departments. This not only helped us avoid potential legal penalties but also reassured customers that their data is handled responsibly."*

Respondent 11 echoed these sentiments, noting the tangible impact of regulatory training on organisational performance: *"Retailers who invested in regulatory training for employees improved compliance scores by around 35%. We've seen far fewer red flags during audits, and it's boosted consumer trust—people appreciate knowing we take data privacy seriously."* Beyond reducing legal risks, these initiatives cultivate a compliance-aware culture, making employees more mindful of how they collect, store, and analyse customer data. This attention to detail ultimately strengthens consumer loyalty and confidence in a retailer's brand.

4.4.3 Competitive Pressure

Competition from both large local chains and international entrants emerged as a significant motivator for analytics adoption, as retailers strive to remain relevant in a rapidly evolving market. Participants viewed analytics as critical for enabling capabilities such as demand forecasting, dynamic promotions, and personalized offers. Respondent 9 emphasized this dynamic, stating that *"Competition undoubtedly motivates us to accelerate analytics adoption. Seeing rivals use advanced analytics for personalized offers pushes us to refine our own capabilities."*

As an executive, Respondent 9 highlights the strategic importance of benchmarking against competitors and aligning analytics initiatives with market trends. Respondent 2 echoed this sentiment, noting that *"Most organizations look to their competitors to identify best practices and trends… failing to adapt risks being left behind."* From an operational perspective, Respondent 2 illustrates the urgency of staying competitive through data-driven decision-making, especially in customer-facing processes like inventory management and promotions.

Smaller retailers, however, face distinct challenges in responding to competitive pressures. Respondent explained that *"We can't just replicate what global giants do. We look for niche areas—like local product curation or unique loyalty perks—where analytics can differentiate us."* This approach reflects the need for strategic selectivity, where smaller players leverage localized analytics solutions to cater to specific consumer segments while avoiding the risks of overextending their resources.

These findings align with Rogers' (2003) DOI theory, which emphasizes the importance of tailoring innovations to specific contexts to maximize compatibility and reduce perceived complexity. However, retailers operating in less saturated or rural markets may experience different competitive dynamics, which could influence their adoption priorities. Further exploration of these variations would provide a more nuanced understanding of how competitive pressure shapes analytics strategies across diverse market contexts.
Competition, both from large local chains and international entrants, stood out as a main motivator for analytics adoption. Participants viewed data-driven capabilities—such as more accurate demand forecasting, dynamic promotions, or personalized offers—as critical for remaining relevant in a rapidly evolving retail landscape.

4.4.4 Cultural & Societal Factors

South Africa's complex socio-cultural environment significantly shapes the adoption of analytics, with diverse languages, varying income levels, and infrastructural disparities presenting unique challenges. Practical obstacles, such as load shedding (periodic power outages) and inconsistent internet coverage, frequently impede real-time data processing and the implementation of cloud-based solutions. Respondent 9 highlighted this challenge, stating that *"Load shedding and uneven broadband access also shape our architectural choices. We might deploy local data caching in stores to handle offline scenarios."*
As an executive, Respondent 9's insights reflect the strategic adjustments necessary to ensure continuity in operations, particularly in a country with significant infrastructural constraints. These adaptive strategies align with the TOE framework, emphasizing the interplay between environmental factors and technology adoption.

Consumer perceptions further influence adoption patterns, particularly in rural or traditional markets where scepticism toward digital platforms is more prevalent. Respondent 3 shared that *"Lingering distrust toward digital platforms, fuelled by fears of data misuse or spam, remains a significant barrier to adoption."* This perspective underscores the responsibility of leadership in fostering consumer trust, particularly through transparent data practices and clear communication of analytics benefits.

According to Rogers' (2003) DOI theory, addressing Compatibility—ensuring analytics initiatives align with societal norms and consumer expectations—is critical for fostering acceptance, especially in diverse cultural contexts. While these findings highlight socio-cultural challenges, deeper exploration is needed to understand how retailers address these barriers. For instance, Respondent 15 mentioned outreach programs targeting rural communities to educate consumers about the benefits of analytics-driven loyalty programs. Expanding on such initiatives would provide a richer perspective on how retailers navigate these dynamics.

Additionally, the trade-offs between investing in infrastructural improvements and prioritizing consumer engagement strategies warrant further investigation. Integrating these insights with literature on rural retail strategies and analytics adoption would offer a comprehensive understanding of how cultural and societal factors shape analytics adoption.

4.4.5 Sustainability & Environmental Initiatives

Sustainability, while not the primary focus for all participants, emerged as a significant secondary outcome of analytics adoption. Data-driven insights enable organizations to reduce waste, optimize supply chains, and manage energy consumption—initiatives that align with both cost reduction and corporate social responsibility (CSR) objectives. Respondent 2 highlighted this alignment, stating that *"Sustainability is becoming a core pillar of our corporate strategy. Analytics helps track our carbon footprint, energy consumption, and waste levels across stores."*

This operational perspective underscores the role of data-driven insights in addressing both financial and environmental goals, reflecting the integration of sustainability into day-to-day business practices. Respondent 8 emphasized the role of demand forecasting in sustainability efforts, explaining that *"By predicting sales accurately, we minimize overstock and reduce food waste, especially in perishables."* As a technical expert, Respondent 8 brings attention to the infrastructural adjustments required to align supply chain practices with sustainability objectives, emphasizing the value of analytics in reducing inefficiencies.

Framing sustainability initiatives as both cost-saving measures and CSR contributions increases their appeal to leadership. Respondent 14 noted that *"If we demonstrate route optimization saves fuel and money, management is more receptive to championing these projects."* This financial perspective highlights the importance of linking sustainability initiatives to tangible ROI, aligning with the TOE framework's emphasis on external pressures influencing organizational readiness. Additionally, Rogers' (2003) DOI theory highlights the Relative Advantage of sustainability-focused initiatives, with clear benefits in cost efficiency, environmental impact, and brand reputation.

Further exploration of specific sustainability projects—such as Respondent 2's efforts to reduce energy consumption through real-time monitoring—could provide valuable insights into how organizations balance the upfront costs of analytics implementation with long-term savings. Additionally, examining variations in sustainability goals across market segments (e.g., urban versus rural operations) would highlight differences in adoption strategies, offering a nuanced view of sustainability-driven analytics adoption.

4.4.6 Consumer Behaviour Insights and Third-Party Collaboration

Two additional themes emerged as significant factors influencing analytics adoption: consumer behaviour insights and third-party collaboration. Retailers commonly leverage loyalty data, transactional histories, and social media sentiment to refine marketing strategies and optimize product offerings. Respondent 2 shared that *"We build consumer profiles by analysing multiple touchpoints—store transactions, online clicks, loyalty programs—to tailor promotions."* This operational perspective highlights the importance of seamless data integration across disconnected systems to enable omnichannel retail strategies. However, challenges remain in bridging these gaps, as noted by Respondent 8, who explained that

"Integrating data from e-commerce platforms and in-store systems remains a significant technical challenge, slowing progress toward unified analytics." These efforts align with the TOE framework's emphasis on the interaction between technological capabilities and environmental demands.

In addition to leveraging consumer insights, several participants emphasized the value of third-party collaborations in overcoming resource constraints and expanding analytics capabilities. Respondent 10 remarked that *"We collaborate with tech vendors for data integration solutions. But we also watch out for vendor lock-in, ensuring we maintain compliance with internal security protocols."* This marketing perspective underscores the strategic considerations of balancing vendor partnerships with maintaining internal control over data security and compliance.
Academic partnerships further enhance organizational capabilities. Respondent 15 described that *"We sponsor capstone projects to analyse anonymized datasets, which not only broaden our perspective but also provide students with valuable real-world experience."* These partnerships reduce the perceived complexity of analytics adoption by providing access to expertise and innovative solutions, as described in Rogers' (2003) DOI theory.

While these strategies offer significant opportunities, challenges such as reliance on third-party vendors, long-term costs, and potential vulnerabilities in data security warrant further exploration. Smaller retailers, in particular, may face difficulties negotiating equitable partnerships with larger technology providers. Expanding the analysis to include successful examples of collaborations and integrating literature on inter-organizational partnerships would provide actionable insights for retailers navigating these dynamics.

4.5 Integration of TOE with the DOI Theory

In addition to the TOE framework, this study applies Rogers' (2003) DOI theory to explain how retail analytics gains traction within organizations. The five attributes—Relative Advantage, Compatibility, Complexity, Trialability, and Observability—appear repeatedly in participants' accounts, elucidating why some analytics initiatives thrive while others stall.

4.5.1 Relative Advantage

Relative advantage reflects the perceived benefits of an innovation over existing practices. Retail analytics, when successfully implemented, promises cost savings, enhanced inventory management, more targeted marketing, and improved customer experiences (Rogers, 2003). Many participants highlighted these tangible benefits as critical for securing leadership buy-in.

Respondent 14 shared that *"A predictive tool that cut down on stockouts by 8% was our breakthrough for leadership buy-in. Once they saw real numbers, the conversation shifted from 'Why do we need this?' to 'How do we scale?'"* This perspective underscores the role of financial analysts in quantifying and presenting analytics-driven outcomes that directly impact bottom-line performance, driving strategic shifts among leadership. Similarly, Respondent 1 emphasized the importance of profit impact, stating that *"If we can demonstrate clear profit impacts, even conservative executives become more open to funding analytics."*

As a technical leader, Respondent 1's role involves not only overseeing implementation but also communicating the business case for analytics to ensure alignment with organizational goals. This highlights how pilot projects and cost-benefit estimates serve as persuasive tools to influence adoption, particularly among cautious decision-makers.

4.5.2 Compatibility

Analytics innovations must align with organizational values, workflows, and user expectations (Rogers, 2003). Even robust solutions may fail if they clash with entrenched practices such as hierarchical decision-making or informal record-keeping. Respondent 14 noted that *"We try to embed analytics into everyday tasks, so it doesn't feel like extra work. For instance, managers see forecasted stock levels in the same system they use to confirm orders."* This approach ensures that analytics tools integrate seamlessly into existing workflows, reducing friction and fostering acceptance.

Respondent 9 highlighted cultural considerations, stating that *"If people feel a model imposes radical changes to how they do business, they resist. We demonstrate how analytics supports, not overrides, their intuition."* As an executive, Respondent 9's perspective emphasizes the importance of aligning analytics initiatives with organizational culture, presenting them as tools for enhancement rather than disruption. This is consistent with Rogers' (2003) Compatibility dimension, where innovations must resonate with existing values and practices to gain traction.

4.5.3 Complexity

Excessive complexity deters adoption, as advanced features may be underutilized if staff find them daunting or if the learning curve is too steep (Rogers, 2003). Respondent 10 stressed that *"If a platform's learning curve is too steep, employees revert to older methods. We need user-friendly dashboards that still deliver robust insights, or else adoption falters."* As a marketing leader, Respondent 10 focuses on ensuring tools meet the practical needs of frontline teams, balancing ease of use with advanced functionality.

Respondent 2 shared operational challenges, stating that *"Some advanced functionalities remain underutilized because employees just want simpler, quick insights. They aren't looking to run neural networks every day."* This highlights the need for tools that provide accessible insights for operational staff while still supporting advanced use cases for data teams. Simplifying interfaces and offering targeted training can mitigate perceived complexity, enabling broader adoption in environments with diverse user groups.

4.5.4 Trialability

Trialability—the degree to which an innovation can be tested on a limited basis—emerged as a recurring strategy for mitigating risk. Participants recounted running small-scale pilots in one store or for a single product category to demonstrate the feasibility and ROI of analytics before broader rollout.

Respondent 3 explained, *"We rely on pilot studies to mitigate risk. If leadership sees a measurable benefit—like cutting stockouts in one product line—it's far easier to replicate in other departments."* As a CEO, Respondent 3's focus on pilot studies reflects their strategic

role in balancing innovation with risk management, ensuring that initiatives align with broader business goals.

Respondent 2 similarly shared, *"One project spent months mapping older database structures to a new analytical engine, but we did it for just one category to prove value before scaling up."* This operational insight emphasizes the technical and logistical challenges of analytics adoption, highlighting the importance of proving value incrementally to build confidence and momentum. These strategies align with Rogers' (2003) Trialability, enabling organizations to refine their approach while reducing uncertainty.

4.5.5 Observability

Observability—how visible the innovation's benefits are to others—proved critical for gaining organizational buy-in. Once analytics initiatives delivered quantifiable improvements, they became significantly easier to scale.

Respondent 1 described the importance of showcasing results, *"When the board sees concrete metrics—like a reduction in time spent on manual reporting—they recognize analytics as a proven value driver."* As a leader responsible for bridging technical solutions with executive priorities, Respondent 1's perspective highlights the role of visible successes in shifting organizational attitudes toward analytics adoption.

Respondent 6 echoed this sentiment, *"We did a five-minute call demonstrating how the new tool saves each manager an hour a day. Once they saw it firsthand, half their concerns disappeared."* This example illustrates how direct, tangible demonstrations of value can alleviate scepticism and generate enthusiasm among operational staff, fostering internal advocacy for broader adoption. Observable successes not only validate the utility of analytics but also serve as internal narratives that encourage departments to explore similar initiatives, reinforcing the momentum for diffusion across the organization.

4.6 Summary of Findings

Chapter 4's findings underscore that the trajectory of retail analytics adoption in South Africa's traditional retail sector is shaped by a complex interplay of technological, organisational, and environmental factors, as illuminated by the TOE framework (Tornatzky & Fleischer, 1990) and Rogers' (2003) DOI theory. These findings highlight both the aspirations and constraints inherent in pursuing data-driven solutions, offering a nuanced portrait of the sector's challenges and opportunities.

Table 4.1 (below) provides a concise synthesis, mapping each sub-theme identified under the three TOE dimensions to Rogers' five DOI attributes. By illustrating how factors such as legacy infrastructure, hierarchical culture, and competitive pressures intersect with perceived relative advantage, trialability, and other DOI attributes, the table clarifies why certain analytics initiatives thrive while others stall.

Technological Dimension

From a technological standpoint, pervasive legacy infrastructures and fragmented point-of-sale (POS) systems emerge as key barriers, complicating real-time data capture and seamless system integration. Rural connectivity constraints exacerbate these issues, as patchy internet

coverage and load shedding compromise reliable data flows. Despite incremental progress—such as mobile analytics and phased cloud migrations—many retailers remain hampered by high costs, limited IT resources, and data security complexities under POPIA.

An additional theme concerns store cards and automated storefronts. While free loyalty cards collect valuable consumer data, a number of respondents noted low ROI when tourists or infrequent shoppers pick up the card but never return, or when analytics teams fail to leverage the data effectively. Simultaneously, advanced "smart" store concepts (e.g., Amazon Go) demand substantial capital, high-resolution cameras, and image-recognition capabilities, all of which many retailers find cost-prohibitive and difficult to justify—especially those contending with legacy systems and limited in-house expertise.

Organisational Dimension
Within organisations, hierarchical cultures and leadership dynamics either facilitate or impede analytics adoption. Strong executive advocacy and structured training can expedite pilot projects, while entrenched silos and lengthy approval chains slow organisation-wide rollout. Data literacy gaps—especially in frontline or rural branches—fuel resistance, as employees may fear job displacement or feel overwhelmed by complex analytics platforms. Respondents repeatedly emphasised the need for targeted education, incentive programmes, and cross-functional collaboration to overcome inertia and cultivate a data-driven culture.

Notably, many senior respondents (e.g., R3, R9) focus on strategic ROI and board approval for analytics initiatives, whereas more junior or mid-level managers (e.g., R2, R7) tend to prioritise day-to-day operational usability. This dichotomy highlights how organisational hierarchies and diverse stakeholder expectations can complicate consistent adoption across all departments.

Environmental Dimension
Externally, financial and budgetary constraints remain paramount: retailers with tight profit margins often favour incremental pilots over sweeping, transformative upgrades. At the same time, competitive pressures from both local and global entrants amplify the need for analytics to refine pricing, promotions, and demand forecasting. In certain markets, high crime rates and socio-economic conditions deter fully automated storefronts, as boards fear both theft and negative perceptions linked to replacing human workers in areas with high unemployment. Moreover, retailers leasing building space confront landlord approvals and extended timelines for structural changes, further complicating the rollout of camera arrays or sensor-based systems.

The regulatory landscape, particularly POPIA, compels retailers to adopt stringent data protection measures, potentially delaying analytics workflows but also fostering consumer trust. Meanwhile, cultural and societal factors—including distrust of digital platforms in rural markets—necessitate transparent data practices and consumer education. Sustainability, while not an immediate priority for all, emerged as a key secondary benefit: optimised demand forecasting, route planning, and energy management can simultaneously reduce operating costs and environmental impact, aligning with corporate social responsibility objectives.

Linking TOE Sub-Themes to DOI Attributes
Viewed through Rogers' (2003) Diffusion of Innovations (DOI) theory, the study highlights the significance of five key attributes in shaping retail analytics adoption. Relative advantage plays a crucial role, as clear demonstrations of return on investment—such as reduced

stockouts or faster reporting—shift perceptions from "Why do we need this?" to "How do we scale?". Compatibility further influences adoption, with analytics tools gaining greater acceptance when seamlessly integrated into existing workflows, such as order-management systems, thereby minimising disruption for frontline staff. However, complexity poses a barrier, as overly sophisticated features and steep learning curves discourage usage, a challenge that can be mitigated by multi-layered platforms designed for different user skill levels, along with robust training initiatives. Trialability emerges as a key enabler, as small-scale pilots and proofs of concept help secure executive buy-in, gradually building momentum for broader rollouts. Finally, observability accelerates adoption, as tangible success stories—such as a pilot store experiencing increased sales—can quickly dispel scepticism and motivate wider organisational uptake.

As summarised in Table 4.1, each TOE sub-theme—ranging from integration challenges to budget constraints—maps onto one or more DOI attributes, illustrating how perceived advantages, user-friendliness, and demonstrable benefits shape the trajectory of analytics diffusion in South Africa's traditional retail sector.

TOE DIMENSION / SUB-THEME	RELATIVE ADVANTAGE	COMPATIBILITY	COMPLEXITY	TRIALABILITY	OBSERVABILITY
TECHNOLOGY (E.G., LEGACY SYSTEMS, INFRASTRUCTURE READINESS)	ROI must be clear to justify upgrades	Must align with existing POS systems	Overhaul can be daunting for older tech	Pilot cloud solutions or mobile apps in 1-2 stores	Measurable improvement in data speed & accuracy
TECHNOLOGY (STORE CARDS & AUTOMATED STOREFRONTS)	Personalized marketing drives advantage	Must fit shopper culture & store layout	Advanced camera/AI systems can deter novices	Implement in select "flagship" stores first	Visible ROI encourages expansion to other branches
ORGANISATION (LEADERSHIP & HIERARCHY)	Executive backing helps justify analytics spend	Tools should integrate with established decision-making channels	Overly complex data outputs can hinder manager adoption	Small-scale POCs can spark interest at the board level	Demonstrated gains in one store create momentum across regions
ORGANISATION (DATA LITERACY, TRAINING, CULTURAL RESISTANCE)	Time-savings & efficiency crucial for staff buy-in	Tools must fit current workflows to reduce pushback	Complexity can breed fear or suspicion	Training pilots reduce resistance, highlight quick wins	Success stories & peer mentoring overcome scepticism
ENVIRONMENT (FINANCIAL CONSTRAINTS, REGULATORY PRESSURES, CRIME RATES)	Clear cost-benefit justifies analytics	Must comply with POPIA & local norms (crime, unemployment)	Additional compliance steps can add perceived complexity	Gradual adoption with close compliance oversight	Substantial external or competitor success fosters greater acceptance

Table 4.2: *Mapping of Key TOE Sub-Themes to Rogers' Five DOI Attributes*

Collectively, these findings illustrate the dynamic tension between aspiration and constraint. Retailers recognise the transformative potential of analytics to optimise inventory, personalise consumer experiences, and gain a competitive edge, yet they grapple with legacy systems, data skills gaps, tight budgets, and regulatory complexities. The added challenges of implementing loyalty cards effectively and deploying high-tech automated storefronts further highlight how contextual barriers—infrastructure, crime rates, building leases, socio-economic factors—often override purely technological readiness.

While this chapter provides an in-depth examination of the drivers and barriers influencing retail analytics adoption, Chapter 5 will synthesise these findings into actionable recommendations. The concluding chapter will outline strategic enablers for more effective adoption, addressing infrastructure gaps, data literacy improvements, executive sponsorship, and market-specific adoption strategies.

Chapter 5: Discussion of Findings

5.1 Introduction

This chapter provides an in-depth analysis of the findings presented in Chapter 4, contextualizing them within the broader research objectives and theoretical frameworks employed in this study. By leveraging the TOE framework and Rogers' DOI theory, the discussion critically examines how South African traditional retailers navigate the challenges and opportunities of analytics adoption. The chapter also explores *newly identified insights*—particularly regarding store/loyalty cards and high-tech automated storefronts—to shed light on the complex realities of implementing advanced analytics in resource-constrained environments. The findings are further interpreted against existing literature to identify areas of alignment, divergence, and contribution to the field.

5.2 Linking Findings to Research Question and Objectives

Research Question 1: *What technological factors influence the adoption of retail analytics in South Africa's traditional retail sector?*
Objective 1: *To analyse technological barriers, such as legacy systems and integration challenges, affecting analytics adoption.*
The study highlights legacy systems, fragmented POS platforms, and limited internet connectivity—particularly in rural areas with load shedding—as major barriers to real-time analytics. High integration costs and tool complexity further hinder scalability, echoing established literature (Davenport & Harris, 2017). In addition, store cards (loyalty programmes) and automated storefronts emerged as new sub-themes: while loyalty cards can capture vast amounts of consumer data, ROI is often low if tourists or occasional shoppers fail to return, or if the data itself remains underutilized. Meanwhile, "smart" store concepts akin to Amazon Go demand high-resolution cameras, advanced image recognition, and robust data analytics—which many local retailers find cost-prohibitive and difficult to justify, aligning with the technology dimension in TOE.
Overall, these findings reinforce the need for user-friendly tools, modular analytics solutions, and affordable infrastructure—all of which must comply with POPIA. This is consistent with the broader technological challenges identified in previous studies, but also underscores how

context-specific constraints (e.g., crime rates, limited budgets) shape high-tech solutions differently in South Africa.

Research Question 2: *How do organizational factors, such as leadership and employee readiness, impact analytics adoption?*
Objective 2: *To evaluate the role of organizational readiness, leadership commitment, and employee skills in facilitating adoption.*
Hierarchical decision-making structures and entrenched silos can hamper cross-departmental collaboration, slowing analytics innovation. Leadership advocacy remains critical: strong executive champions accelerate pilot projects, whereas boards focused on short-term ROI often delay or narrow the scope of implementation. At the same time, employee resistance—rooted in fears of job displacement and *perceived* oversight—surfaces as a key obstacle, particularly in frontline roles unfamiliar with data-driven workflows (Chandramana, 2017). The new findings on loyalty card programmes also highlight the organisational gap: while these programmes are launched with the aim of collecting data, they often lack strategic follow-through (i.e., robust analytics teams or training to glean actionable insights). Consequently, the data sits siloed or underutilized, indicating that data literacy and process integration are just as critical as the technology itself. These organizational dynamics reflect the Complexity and Compatibility attributes of DOI theory (Rogers, 2003), showing how staff readiness and leadership priorities can either reinforce or undermine adoption efforts.

Research Question 3: *What environmental factors, including market dynamics and regulatory pressures, shape the adoption of retail analytics?*
Objective 3: *To examine the influence of environmental pressures, such as competition and infrastructure limitations, on adoption decisions.*
Findings confirm that competitive pressures drive interest in analytics for personalised promotions and proactive demand forecasting. POPIA compliance compels retailers to establish clear data governance structures, balancing innovation with privacy obligations. Socio-economic realities (e.g., high unemployment, crime rates) further shape the feasibility of advanced, camera-based solutions like automated storefronts. Retailers leasing property also face landlord approvals and infrastructure constraints, adding bureaucratic layers that can stall large-scale technology rollouts.
These insights reaffirm the Environment dimension in TOE—external forces such as market demands, socio-cultural conditions, and regulatory mandates substantially influence adoption. They also highlight Relative Advantage and Trialability from DOI: while automated storefronts offer potential labour savings, high crime risks and negative perceptions surrounding job losses complicate the business case. As a result, incremental pilots in select, well-monitored locations emerged as a common strategy.

Research Question 4: *How can traditional retailers address barriers to successfully adopt and implement analytics?*
Objective 4: *To propose actionable recommendations for traditional South African retailers to overcome adoption challenges and leverage analytics for competitive advantage.*
Key recommendations include piloting incremental projects with visible ROI, fostering cross-functional collaboration, and partnering with technology providers or academic institutions for training and skill-building. Sustainability also surfaces as a secondary driver, with analytics facilitating waste reduction, energy optimization, and cost control—thus aligning both operational and CSR goals. Moreover, deploying smart store concepts or advanced analytics in a limited number of flagship stores may mitigate risk, showcase feasibility, and

address safety concerns. These targeted rollouts align with Trialability (Rogers, 2003), demonstrating tangible benefits before large-scale adoption.

5.3 Discussion of Findings by Dimension

5.3.1 Technological Dimension

TECHNOLOGY DIMENSION	INTERSECTING DOI ATTRIBUTES	SA RETAIL
LEGACY INFRASTRUCTURE	Compatibility, Complexity	Outdated POS systems and poor integration increase Complexity and reduce Compatibility.
CLOUD OR MOBILE ANALYTICS	Trialability, Relative Advantage	Firms piloting cloud solutions can trial innovations before full adoption, demonstrating value.
SYSTEM USABILITY	Complexity	When analytics tools are hard to understand, Complexity deters staff uptake

Table 5.3.1: The technological characteristics and readiness of the innovation.

The research underscores how legacy infrastructures, fragmented POS systems, and load shedding hamper real-time analytics, supporting earlier scholarship on infrastructure readiness (Davenport & Harris, 2017). Cloud-based and mobile solutions appear promising but remain unevenly adopted due to integration costs, data security concerns under POPIA, and staff hesitancy over “new” platforms.

Adding to these complexities are loyalty/store cards and automated storefronts. While loyalty cards theoretically provide rich consumer data, respondents reported inconsistent usage by shoppers—leading to gaps in longitudinal data—or insufficient data analysis follow-through. This mismatch of *data potential* and *analytical execution* highlights the lack of synergy between marketing objectives and in-house technical capabilities. Meanwhile, automated storefronts—often lauded in global contexts (e.g., Amazon Go)—face high capital expenditures and specialized technology demands (machine vision, real-time analytics). In resource-constrained areas with crime concerns and limited skilled personnel, these advanced systems appear too complex (Rogers’ Complexity) to adopt wholesale.

From a DOI perspective, retailers will need simple, modular solutions that demonstrate immediate payoffs (Relative Advantage), fit existing workflows (Compatibility), and can be trialled in low-risk settings (Trialability). This aligns with extant research suggesting that perceived complexity deters adoption unless supported by robust training and incremental rollouts (Chandramana, 2017).

5.3.2 Organizational Dimension

ORGANIZATION DIMENSION	INTERSECTING DOI ATTRIBUTES	SA RETAIL
CROSS-FUNCTIONAL COLLABORATION	Observability	Visible success in one unit (e.g. better stock forecasting) encourages uptake in others.
STAFF SKILLS / DATA LITERACY	Complexity, Compatibility	Low literacy increases perceived difficulty (Complexity), hindering integration.
LEADERSHIP SUPPORT	Relative Advantage, Observability	Leaders who champion analytics show others its value, making benefits more visible.
EMPLOYEE RESISTANCE	Complexity, Compatibility	Concerns over surveillance or job loss reduce perceived fit with organisational culture.

Table 5.2.3: Internal characteristics that influence adoption.

Leadership and data literacy emerged as pivotal influences, resonating with the Organisation dimension of TOE. While some organisations employ centralised analytics teams to standardise practices, siloed decision-making often persists, particularly when departmental heads fear that analytics might expose inefficiencies. Employee resistance also remains high: staff may worry about job displacement or interpret analytics tools as a form of performance surveillance. This is intensified in loyalty-card or automated-store contexts, where advanced data collection can raise privacy or oversight concerns among frontline workers (Randhawa, 2019).

To better understand this resistance, it is useful to draw on established change management theories. Lewin's three-phase model, unfreezing, changing, and refreezing, frames resistance not as a barrier but as a symptom of inadequate preparation for transformation. In many of the participating firms, resistance appeared strongest at the unfreezing stage, where employees were not adequately convinced of the value of analytics or were insufficiently prepared for its implications. Similarly, Kotter's 8-Step Change Model offers relevant insight: steps such as establishing a sense of urgency, building a guiding coalition, and communicating a clear vision were often lacking in the organisations studied (Kotter, 1996). Where leadership failed to create alignment and reassurance, staff members viewed analytics tools with scepticism. Conversely, firms that actively engaged employees, clarified the strategic purpose of analytics, and highlighted personal and organisational benefits saw higher acceptance and internal advocacy.

Crucially, the study finds that top-down directives alone are insufficient: cross-functional collaboration, targeted training, and incentives tied to data usage are more effective in encouraging widespread adoption. When store managers or marketing leads see concrete evidence of analytics-driven improvements—such as more accurate stock replenishment—they gradually become internal advocates (Observability). Similarly, structured training mitigates Complexity by breaking down advanced tasks (e.g., interpreting machine-learning predictions) into digestible lessons aligned with daily responsibilities.

5.3.3 Environmental Dimension

ENVIRONMENT DIMENSION	INTERSECTING DOI ATTRIBUTES	SA RETAIL
REGULATORY ENVIRONMENT	Compatibility	POPIA compliance may slow adoption, especially if systems are not built with data privacy in mind.
MARKET COMPETITION	Relative Advantage	Pressure from e-commerce pushes traditional retailers to see analytics as a strategic necessity.
ECONOMIC CONSTRAINTS	Trialability, Complexity	Financial strain limits ability to experiment; solutions must be simple and affordable to trial.

Table 5.3.3: External factors influencing the firm's decision-making.

Exogenous factors—competitive pressures, regulatory demands, and socio-economic realities—heavily shape analytics adoption paths in South Africa. Competition from global chains and e-commerce platforms spurs interest in advanced analytics, while POPIA compels meticulous data handling. Unique to the local context, high crime rates and leasing constraints dissuade broad deployment of fully automated stores. Board reluctance around automation also ties into high unemployment rates, as purely automated solutions risk negative community reactions.

As a result, retailers typically opt for incremental pilots—testing either advanced loyalty schemes or partial automation (like self-checkout with camera oversight) in safe, high-traffic stores. These localized approaches reduce risk, enable real-time troubleshooting, and provide compelling Observability for decision-makers. Aligned with TOE's environment dimension, these steps highlight how external constraints (infrastructure, compliance, socio-economic factors) can outweigh purely technological readiness, underscoring the interplay between adoption potential and real-world viability (Gupta & Rani, 2019).

5.4 Comparison with Existing Literature

Overall, the findings align with prior research emphasizing technological readiness, organizational capability, and environmental pressures as critical determinants of analytics adoption (Tornatzky & Fleischer, 1990; Davenport & Harris, 2017; Rogers, 2003). Much like earlier studies, this investigation underscores the role of legacy systems, infrastructure gaps, leadership advocacy, and employee readiness in shaping technology uptake. However, the study also uncovers several context-specific nuances that appear underexplored or overlooked in mainstream literature:

Tourist Footfall and Loyalty Card ROI
While loyalty or "store" cards are well-documented in marketing literature for gathering consumer data and fostering brand loyalty (Randhawa, 2019), most studies assume consistent local usage. In contrast, multiple interviewees pointed out that tourists or infrequent shoppers collect the card but never return, diluting the dataset and undermining the ROI. This phenomenon, rooted in South Africa's particular tourist inflows and fragmented retail geographies, suggests that the global loyalty-program playbook may require region-specific modifications. Existing research rarely addresses such transient card usage, highlighting a literature gap regarding how mobile populations, vacationers, or one-off consumers affect the viability of analytics-driven loyalty schemes.

Building Leases and Physical Modifications
A significant number of respondents emphasized how leasing constraints block or delay structural changes required for camera installations or sensor-based "smart" store technologies. Traditional analytics-adoption frameworks (e.g., TOE) often presume that retailers own or can freely modify their store premises (Gupta & Rani, 2019). In reality, landlord approvals, lease restrictions, and protracted bureaucratic processes can overshadow purely technological readiness, limiting the speed or scale of analytics rollouts. Mainstream literature tends to gloss over this property-dynamics factor, pointing to an *unrecognized barrier* that specifically impacts retailers in markets where store ownership is not the norm.

Crime and Societal Constraints for Automation
Many global case studies on "smart" or fully automated storefronts (e.g., Amazon Go) assume relatively low-theft contexts and stable socio-economic conditions (Delen & Zolbanin, 2018). Interview data reveals that in high-crime areas, advanced camera systems may actually prove a liability if equipment is stolen or vandalized, or if consumers feel mistrusted. The prospect of a *fully unmanned store* also raises unemployment and public-perception issues—unique societal factors that many Western-centric studies do not investigate. This underscores the need for locally adaptable automation strategies that consider both security costs and community sentiment, thus expanding upon the standard adoption frameworks that rarely address high-crime contexts in detail.

Socio-Economic Perceptions of Job Displacement
Existing literature often discusses resistance to analytics as a function of fear of the unknown, lack of digital literacy, or loss of decision-making autonomy (Chandramana, 2017). However, the respondents shed light on job displacement anxieties, particularly acute in South Africa's high-unemployment environment. Employees and even boards fear public backlash if automation is perceived as "replacing" local workers. This social-labour dimension rarely features in mainstream analytics adoption research, revealing a gap in understanding how local labour market conditions can slow or redirect technology projects.

Costs of Storing and Analyzing Video Feeds
While global literature often praises video-analytics technologies and AI-driven store monitoring for creating frictionless experiences (Gupta & George, 2016), few studies delve into the long-term data-storage and bandwidth burden that such solutions entail—especially in areas with limited connectivity and high data costs. Respondents in this study repeatedly cited ongoing cloud-storage bills, compliance overhead (under POPIA), and the specialized skill sets needed to maintain such systems. This underscores a practical cost factor—distinct from mere hardware investments—that remains underrepresented in academic discussions around AI-driven retail.

Underserved Rural Branches and Pilot-Driven Approaches
While incremental or pilot-based deployments are widely promoted (Rogers, 2003), few studies deeply examine how rural store branches—confronting load shedding and intermittent bandwidth—execute these pilots in practice. Interviewees described "offline-first" or mobile analytics solutions as short-term workarounds. This nuance adds depth to the notion of Trialability (DOI), illustrating that partial or phased analytics deployment isn't just a strategic preference but sometimes the only feasible path. Research that overlooks rural constraints may understate the complexity of pilot rollouts and overestimate the viability of uniform, chain-wide solutions.

Sustainability and CSR as Emerging Motivators

Most analytics literature spotlights operational efficiency and customer-centric benefits (Naidoo & Gasparatos, 2019). However, the findings highlight how some South African retailers frame analytics as supporting energy optimization, waste reduction, and overall CSR efforts. This intersection of operational ROI with environmental responsibility is increasingly recognized (Bertsimas & Kallus, 2020), yet there is limited research detailing how resource-constrained retailers balance the cost of analytics investment with long-term sustainability goals. The interviews illuminate a dual incentive—cost-saving + CSR—that global literature has not fully explored in emerging-market contexts.

In sum, while the overarching challenges and drivers identified in this study—*such as cost constraints, leadership buy-in, and data-security concerns*—resonate with well-documented literature, several interview-specific insights challenge the one-size-fits-all narrative often found in global case studies. By revealing the unique roles of building leases, tourist card usage, job-displacement anxieties, rural connectivity, and advanced camera storage overhead, these findings underscore the need for locally adaptive and socially attuned frameworks. They further suggest that mainstream adoption models could benefit from greater granularity in addressing regional socio-economic factors, infrastructure disparities, and the full life-cycle costs of high-tech solutions.

5.5 Practical Implications

The findings of this study provide actionable insights for a wide range of stakeholders in South Africa's traditional retail sector, underscoring transformative strategies that can accelerate analytics adoption while addressing infrastructural, cultural, and financial barriers. These insights move beyond conventional operational efficiencies and touch upon newly identified opportunities—including mobile-first analytics, hybrid storage models, and sustainability tracking—all of which prove crucial for retailers striving to remain competitive and socially responsible in a complex environment.

5.5.1 Implications for Retailers

From a practical standpoint, South African retailers can benefit by starting with incremental pilot projects that have visible returns on investment (ROI). By focusing on smaller-scale implementations—such as introducing analytics for demand forecasting in a single store—retailers reduce financial risk while showcasing tangible successes to both leadership and frontline employees. Such pilot projects not only build internal advocacy but also help retailers refine their data strategy, ensuring that eventual expansions to multiple outlets are supported by proven models and clear cost-benefit evidence.

A notable theme emerging from the interviews is the importance of mobile-first analytics as a cost-effective bridge to more advanced data platforms. Many local retailers, particularly those constrained by legacy infrastructures or unstable connectivity, have found that mobile dashboards and real-time sales tracking apps can provide immediate insights without a complete IT overhaul. This approach suits regions plagued by load shedding or patchy internet, as staff can collect and interpret sales data on handheld devices, often operating offline until connectivity stabilizes. In parallel, organizations experimenting with offline-first or hybrid data-storage solutions can further bolster resilience by locally caching transaction

data and syncing it to the cloud periodically—a practice that diminishes disruptions while preserving comprehensive, high-quality datasets.

Additionally, the sustainability dimension of retail analytics is becoming increasingly relevant. Some interviewees highlighted the ability to track energy consumption, food waste, or ethical supply chains through analytics, indicating that a well-structured data strategy can align with both cost-reduction and corporate social responsibility (CSR) goals. For instance, forecasting sales patterns helps reduce perishable waste, and route optimization curtails fuel expenses. By integrating these objectives into analytics initiatives, retailers tap into emerging consumer demands for environmentally responsible business practices, thereby differentiating themselves from competitors.

Crucially, the study also reveals that technical advances must be accompanied by a leadership-driven cultural shift for analytics to take root. While some organizations focus heavily on software and training, employees remain sceptical unless senior leaders establish clear data-driven metrics and visibly endorse analytics-based decision-making. When executives embed analytics throughout strategic planning—tying departmental or store-level targets to specific analytics outcomes—uptake accelerates. In the same vein, tailored training programs and incentive structures (such as bonuses tied to data-use milestones) help overcome deep-seated resistance, especially among frontline staff concerned about job displacement or performance monitoring. By emphasizing the collaborative nature of analytics—as an augmentation tool rather than a replacement—retailers can successfully foster a data-centric culture.

Moreover, strategic expansion of analytics must consider each retailer's scale and budget. Smaller businesses can roll out localized solutions—like niche loyalty programs or curated product offerings—using analytics tools that require fewer capital investments, thus differentiating themselves without committing to costly enterprise platforms. Even for larger retailers, incremental expansions offer a pragmatic path, gradually embedding analytics into day-to-day workflows and integrating them seamlessly with existing POS or CRM systems.

5.5.2 Implications for Policymakers

The urgent infrastructural gaps identified in the study—ranging from uneven broadband access to recurrent load shedding—underscore the crucial role that policymakers can play in enabling analytics adoption. Government-backed initiatives to upgrade connectivity in rural areas or provide incentives for backup power solutions (e.g., subsidizing solar or battery systems for small retailers) would help level the playing field, allowing retailers across diverse geographies to leverage real-time data. Policymakers should also strive to balance compliance mandates (such as POPIA) with room for innovation, perhaps by streamlining regulatory processes for pilot analytics projects. Such measures could stimulate local economic growth, boost retail competitiveness, and support the broader push toward digital transformation.

5.5.3 Implications for Technology Providers

For technology providers aiming to serve South African retailers, the study highlights a need for solutions customized to local market constraints. In practice, this entails designing modular software capable of integrating with legacy POS systems and supporting offline capabilities during connectivity outages. Providers can further collaborate with retailers and

academic institutions to co-develop cost-effective tools or specialized features (e.g., image recognition for partial automation) that directly address high crime rates, limited budgets, or staff training deficits. By offering robust after-sales support, user-friendly interfaces, and localized analytics content (e.g., region-specific demand forecasting modules), technology vendors stand to build long-term, trust-based relationships with retail clients in resource-constrained markets.

5.5.4 Implications for Academic Institutions

Academic institutions play a pivotal role in upskilling the workforce and fostering innovation. Through capstone projects, internships, or specialized retail analytics certification programs, universities can help retailers cultivate the local talent needed to translate data into actionable insights. Students gain real-world experience, while retailers benefit from fresh approaches and targeted problem-solving. Collaborative research endeavours can also inform the development of regionally relevant analytics frameworks—especially around mobile-first or offline-first architectures—and expand the broader academic discourse on how socio-economic contexts shape technology adoption.

5.5.5 Strategic Benefits and Future Outlook

Ultimately, the strategic advantages of well-executed retail analytics extend well beyond operational efficiency. Customer retention is strengthened by proactive engagement strategies, sustainability objectives are met through waste reduction and ethical supply-chain monitoring, and risk management improves via fraud detection and safer logistical practices. Together, these capabilities bolster profitability while reinforcing the brand reputation of South African retailers—particularly in a climate where consumers increasingly value ethical and environmentally conscious business practices.

Yet, these benefits hinge on addressing persistent challenges, including cost constraints, data literacy gaps, and cultural resistance. Retailers looking to evolve into data-driven organizations must undertake phased rollouts, harness mobile-first analytics as a stepping stone, and proactively communicate the tangible benefits of analytics to both employees and customers. Policymakers, technology vendors, and academic partners each have integral roles to play in bridging infrastructural divides, co-creating localized solutions, and fuelling the leadership-driven cultural shifts necessary for widespread analytics adoption.

5.6 Limitations and Future Research Directions

This study is limited by its qualitative design, which may not capture the full diversity of experiences across the sector. While interviews provided valuable insights into the perspectives of participants, they rely on self-reported data, which may introduce biases, such as social desirability bias or selective recall. A mixed-methods approach in future research could strengthen the findings by quantifying the impact of specific factors on analytics adoption rates, providing a more robust empirical foundation.

The geographic focus on South Africa’s traditional retail sector further limits the generalizability of the findings. The study’s context-specific nature, influenced by South Africa’s unique socio-economic realities, such as load shedding, income disparities, and rural connectivity challenges, may not reflect conditions in other regions or countries. Comparative studies across different regions or countries could provide a broader understanding of the dynamics influencing analytics adoption and highlight context-specific variations.

From a theoretical perspective, the reliance on the TOE framework and Rogers' DOI theory provides a structured lens for analysis but may also constrain the interpretation of the findings. Alternative frameworks, such as the Actor-Network Theory or Resource-Based View, could offer complementary insights, particularly into the interplay of human and non-human actors or the strategic resource allocation decisions shaping analytics adoption.

Finally, practical constraints, including limited access to participants in leadership or highly technical roles, may have restricted the depth of the data collected. These perspectives could provide more granular insights into decision-making processes, particularly in resource-constrained or highly competitive environments. Expanding the participant pool in future research to include policymakers, technology vendors, and frontline employees would enrich the understanding of the multi-stakeholder dynamics at play in analytics adoption.

5.7 Conclusion

The discussion in this chapter highlights the intricate interplay of technological, organizational, and environmental factors in shaping analytics adoption in South Africa's traditional retail sector. By applying the TOE framework and DOI theory, this study provides a nuanced understanding of the barriers and opportunities faced by retailers. While challenges persist, particularly in rural and resource-constrained contexts, the strategic alignment of analytics with operational goals, regulatory compliance, and sustainability objectives presents significant potential for growth. These findings set the stage for the recommendations outlined in the next chapter, aimed at fostering a more inclusive and impactful analytics landscape.

Chapter 6: Conclusion

6.1 Synthesis of Key Insights

This study set out to explore the adoption of retail analytics in South Africa's traditional retail sector, examining the influence of technological, organisational, and environmental factors through the TOE framework (Tornatzky & Fleischer, 1990) and Rogers' (2003) DOI theory. The findings reveal a complex interplay between infrastructure limitations, workforce readiness, market pressures, and broader socio-economic conditions, illustrating both the potential and the barriers associated with analytics adoption.

From a technological perspective, retailers struggle with legacy POS systems, inconsistent internet connectivity, and frequent power outages due to load shedding, all of which hinder real-time data capture and advanced analytics deployment. While some organisations have experimented with store loyalty cards and automated storefronts to enhance data collection, these solutions have produced inconsistent returns, particularly in contexts with tourist-driven footfall or high capital costs. Additionally, concerns surrounding data security and regulatory compliance under POPIA introduce another layer of complexity, as businesses navigate the balance between leveraging consumer insights and adhering to legal mandates.

On an organisational level, leadership commitment and cross-departmental collaboration emerge as critical enablers of analytics adoption, yet cultural resistance remains a persistent challenge. Employees express anxieties over job displacement, particularly in store management and inventory planning roles, leading to hesitancy in fully integrating analytics-

driven decision-making. Furthermore, divergent priorities between senior executives and operational teams illustrate a gap in how analytics adoption is perceived—while executives prioritise ROI and long-term strategy, frontline staff are more concerned with daily usability and workflow disruptions. The findings also highlight that successful adoption depends not just on technical skills training but on a broader change-management approach that fosters a data-driven culture within retail organisations.

Externally, financial constraints, crime rates, and regulatory hurdles continue to shape the pace and scope of adoption. Many retailers operate under tight profit margins, leading them to favour incremental pilot programs over sweeping digital transformations. Additionally, leasing agreements and landlord approvals introduce unexpected barriers, as retailers seeking to deploy sensor-based analytics or surveillance infrastructure must navigate complex negotiations before implementing technological upgrades. Societal factors, such as consumer scepticism toward automation, further complicate adoption, particularly in areas with high unemployment, where retailers remain cautious about public perceptions of job-reducing technologies.

Taken together, these findings illustrate a tension between the promise of analytics and the practical constraints imposed by infrastructure limitations, budgetary restrictions, and workforce readiness. While analytics adoption is largely driven by Relative Advantage, Compatibility, and Trialability (Rogers, 2003), retailers must carefully navigate context-specific constraints to ensure that new technologies align with both business objectives and socio-economic realities.

6.2 Limitations of the Study

The research employed a qualitative design, prioritising depth over breadth. While semi-structured interviews yielded rich, context-specific insights, the reliance on self-reported data introduces potential biases, including social desirability bias (Bryman & Bell, 2015) and selective recall. A mixed-methods approach, incorporating quantitative surveys or system usage logs, could provide a more empirical assessment of analytics adoption patterns.

Second, the study's geographic and sectoral focus presents limitations regarding generalizability. The findings are deeply contextualised within South Africa's traditional retail sector, where challenges such as load shedding, rural connectivity gaps, and crime-related concerns play a significant role in shaping technology adoption. However, these barriers may not be equally applicable in other emerging markets or within modern, omnichannel retail models. Comparative studies across different regions—both within Africa and internationally—could provide broader insights into adoption trends and determine whether issues such as leasing approvals, tourist-driven loyalty card usage, or socio-economic resistance to automation hold relevance beyond the South African context.

Third, the study's theoretical lens is another area where additional perspectives could yield new insights. While the TOE framework and DOI theory provided a structured approach to understanding adoption patterns, alternative perspectives—such as Actor-Network Theory (ANT) or the Resource-Based View (RBV)—could highlight different dynamics. For instance, ANT might explore how non-human actors (e.g., camera infrastructure, software interfaces) influence adoption, while RBV could assess how intangible assets like workforce skills or brand trust shape the success of analytics deployment. Future research employing

these alternative frameworks could complement the current findings by offering new analytical dimensions on technology adoption.

Lastly, stakeholder representation poses a limitation. While the study incorporated diverse perspectives from executives, managers, and analytics specialists, certain key stakeholders—including landlords, policymakers, and frontline employees—were underrepresented. Given that leasing agreements and property ownership structures were cited as barriers to implementing sensor-based analytics and surveillance, future research could engage commercial property managers to better understand the real-estate constraints affecting in-store analytics deployment. Additionally, gaining deeper insights from consumer groups and retail workers could provide a more holistic view of how analytics adoption impacts both shopping experiences and employment conditions.

By acknowledging these limitations, this study provides a clear foundation for future inquiry, encouraging broader, more diverse research approaches that refine and expand upon the findings presented here.

6.3 Recommendations for Future Research

A mixed-methods approach could enhance the robustness of analytics adoption findings by incorporating quantitative surveys alongside qualitative interviews. Such research could measure adoption rates, ROI calculations, and actual system usage, providing a more empirical validation of adoption enablers and barriers. Additionally, a comparative study across regions could examine whether factors like crime concerns, building lease constraints, and workforce resistance manifest similarly in other emerging markets or developed economies. A multi-case analysis spanning South Africa, other African nations, and BRICS economies could shed light on contextual commonalities and divergences.

Future research could also benefit from alternative theoretical frameworks. While TOE and DOI effectively structure adoption factors, applying Actor-Network Theory, Institutional Theory, or the Resource-Based View could provide new perspectives on how stakeholder dynamics, regulatory environments, and firm-specific resources influence adoption outcomes. Similarly, longitudinal case studies tracking pilot projects could capture the evolving nature of analytics adoption, offering insights into how organisational resistance, cost structures, and technology performance change over time.

Finally, research into the societal impact of analytics adoption is crucial. This study identified fears surrounding automation, job displacement, and algorithmic decision-making in high-unemployment areas, suggesting the need for deeper exploration into retail workforce transformations. Partnering with labour organisations, governmental bodies, or consumer advocacy groups could provide valuable insights into how analytics-driven automation is perceived by local communities and what measures can be implemented to balance technological progress with socio-economic well-being.

By pursuing these research directions, future studies can expand the current understanding of retail analytics adoption, ensuring that technology implementation is both effective and contextually sensitive in emerging markets. Ultimately, such efforts will contribute to a broader discourse on how analytics can be leveraged to enhance operational efficiency while aligning with societal and economic realities.

6.5 Final Reflections and Closing Remarks

In concluding this research, it is clear that retail analytics holds significant promise for South Africa's traditional retailers, offering pathways to optimise inventory, enhance customer engagement, and foster data-centric cultures. Yet the practical realities—from legacy infrastructures and tight budgets to regulatory complexities and cultural resistance—underline that successful adoption demands much more than simply installing new software. Key factors such as leadership support, incremental pilot projects, employee training, and context-aware solutions (e.g., mobile-first or offline-ready) emerged as vital enablers, while recognition of local socio-economic conditions—including load shedding, crime rates, and leasing constraints—proved crucial for tailoring strategies effectively.

Ultimately, the study's findings illustrate that harnessing analytics in this context is both a technological and cultural journey, requiring alignment of vision, resources, and stakeholder commitment. By continuing to explore alternative frameworks, employing mixed-methods approaches, and broadening participant pools to include policymakers, technology vendors, and frontline staff, future research can deepen understanding and spark further innovation. The insights presented here—particularly on bridging infrastructure gaps, investing in workforce readiness, and balancing automation with societal needs—serve as a springboard for practitioners and researchers to advance a more inclusive, data-driven future in South Africa's retail sector.

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UNIVERSITY OF CAPE TOWN
FACULTY OF COMMERCE
Igniting Knowledge and Opportunity

COMPG05: Certification of Corrections

Student Full Name	Shaun Moloi
Student Number	mlxtum003
Dissertation Title	Bridging the Gap: Factors Driving Retail Analytics Adoption in Traditional Retail Businesses
Department	Information Systems

I/We, the undersigned supervisor/s, hereby certify that the above-mentioned candidate has completed the corrections to the Masters dissertation to my/our satisfaction in accordance with the recommendations of examiners.

In the case of a pass with corrections, a schedule of the completed corrections is attached. Where any corrections have not been made, an explanation is given.

The copy of the corrected dissertation has been uploaded on PeopleSoft for OpenUCT purposes.

All the above is subject to the HDC Chair's approval where applicable.

	Name	**Signature**	**Date**
Supervisor 1	**A/Prof. Adheesh Budree**		**27/06/2025**
Supervisor 2			

Commerce Faculty: Schedule of Corrections

Student Full Name:	Tumelo Shaun Moloi
Student Number:	MLXTUM003
Dissertation Title:	Bridging the Gap: Factors Driving Retail Analytics Adoption in Traditional Retail Businesses
Degree:	Master of Commerce
Department:	Information Systems
Supervisor(s):	Adheesh Budree

Examiners' Recommendations	Student's Responses	Chapter / Section / Page
The title, 'Bridging the Gap: Factors Driving Retail Analytics Adoption in Traditional Retail Businesses,' presents two related challenges. The phrase 'Bridging the Gap' does not appear to be a major finding or framing device in the body of the dissertation, and thus may be misleading.	Noted. The phrase "Bridging the Gap" has been intentionally retained as part of the title, as it reflects a central thematic concern of the study: the divide between traditional South African retailers and their digitally mature global counterparts. While the phrase may not have been explicitly repeated throughout the dissertation, it conceptually anchors the investigation	No change made.
Clearly specify the number and types of participants involved in the study to enhance transparency around data collection. Detail the roles or job titles of the participants (e.g., managers, analysts, etc.) instead of broadly stating "large and mid-tier retailers."	The abstract has been revised to specify participant details clearly.	Abstract, Page 3
Problematize the assumption that analytics adoption is universally beneficial by adding a paragraph discussing potential trade-offs or local tensions. Strengthen the theoretical grounding in the significance section by explicitly mentioning how empirical findings may refine or extend existing technology adoption theories (TOE and DOI) in the emerging market context of mid-tier retailers.	The Introduction (specifically, the Problem Statement and Significance sections) has been expanded to explicitly challenge the assumption of universal benefit in retail analytics adoption, acknowledging potential trade-offs and local tensions. Additionally, the Significance section now explicitly notes how empirical findings from this study contribute to refining the TOE and DOI models, providing insights tailored to the unique context of mid-tier retailers in emerging markets like South Africa.	Chapter 1 - Section 1.2: Problem Statement, Section 1.3: Research Purpose and Significance, pages 9–10
Deepen critical engagement with the literature by interrogating how constructs such as compatibility, complexity, organisational readiness, and employee resistance are operationalised in empirical studies. Clarify the complementarity and boundaries of the TOE and DOI frameworks to avoid analytical redundancy. Justify the combined use of both frameworks with reference to prior studies that employed both. Explicitly address overlaps between constructs such as complexity (DOI) and technology readiness (TOE).	A new section has been added to address this feedback. It includes a discussion of how empirical studies define and measure constructs like compatibility, complexity, organisational readiness, and employee resistance. The section also critically explains the rationale for using both TOE and DOI frameworks, outlines their distinct contributions.	Chapter 2: Section 2.5.4 Critical Reflection on Frameworks and Construct Measurement (new section added), Page 27

The dissertation incorrectly claims to follow an inductive research approach, despite coding data directly into TOE and DOI categories from the design of the research instruments through to analysis. This is inconsistent with inductive logic, which avoids predefined categories.	The section has been revised to clarify that the study adopts an abductive research approach, rather than a purely inductive one. A paragraph has been added explaining abductive reasoning, referencing key literature and justifying its suitability for the study's theoretical and empirical aims.	Chapter 3 - Section 3.1: Research Philosophy and Approach
The dissertation lacks transparency around case selection logic. It is unclear why the three firms were selected and how they differ in terms of geography, digital maturity, and strategic orientation. The examiner also requested a clearer articulation of how these firms reflect meaningful variation for qualitative analysis.	A new integrated section titled Sampling and Case Selection has been added to Chapter 3. This section explains the purposive sampling approach and provides justification for focusing on three formal retail chains	Chapter 3 - Section 3.1.4: Case Selection and Scope
The discussion on employee resistance could potentially be improved and enriched by more direct engagement with change management theory (e.g., Kotter or Lewin), especially since the findings touch on psychological and cultural dimensions of resistance.	The discussion on employee resistance has been expanded to incorporate relevant insights from change management literature. Specifically, Lewin's (1947) three-stage model and Kotter's (1996) 8-Step Change Model are used to interpret the psychological and cultural dimensions of resistance observed in the case studies.	Chapter 5 - Section 5.3.2: Organizational Dimension
I recommend creating and inserting a final integrative diagram/framework showing how TOE and DOI intersect in the South African context to elevate the analytical clarity.	Rather than a single final diagram, I've incorporated structured tables within the discussion segments of each TOE pillar. These tables clearly illustrate how the TOE framework intersects with the attributes of the DOI theory in the South African retail context.	Chapter 5 - Section 5.3.1, 5.3.2, 5.3.3