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The impact of digital maturity and digital innovation on supply chain resilience in the South African FMCG industry

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ABSTRACT

Digitalisation and its implications on supply chain resilience have been well explored in the context of developed countries. Industries such as the Fast-Moving Consumer Goods (FMCG) industry are highly competitive, and supply chain disruptions harm an organisation’s ability to sustain and grow its market share. This study investigated the relationship between digital maturity and supply chain resilience in South Africa, an emerging market in the FMCG industry. It also investigated the mediation role of digital innovation on the relationship and the influence of company size as a moderator variable.

Three hypotheses were developed using insights from previous studies and the theories of dynamic capabilities and resource-based view. While interpreting the three hypotheses, a fourth hypothesis on the moderation role of company size emerged. Data were collected using a quantitative online survey tool, with purposive sampling employed. A total of 206 valid responses from supply chain managers were collected, analysed, and interpreted using structural equation modelling and regression analysis.

The result of the study supported a strong positive relationship between digital maturity and digital innovation. A similar relationship between digital innovation and supply chain resilience was also supported. Furthermore, the study found that the direct relationship between digital maturity and supply chain resilience was insignificant but moderated by company size. This deviated from previous studies conducted in developed markets and/or with small and medium enterprises. The key drivers of digital maturity and supply chain resilience are identified, and the practical implications for key stakeholders and future research directions are outlined.

KEYWORDS

Keywords: Digital Maturity, Digital Innovation, Supply Chain Resilience, FMCG Industry, South Africa

DECLARATION

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

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AMOS	- Analysis of Moment Structures
AVE	- Average Variance Extracted
CB-SEM	- Covariance-based structural equation modelling
CFA	- Confirmatory Factor Analysis
CFI	- Comparative Fit Index
CMB	- Common method bias
CR	- Composite Reliability
df	- Degrees of Freedom
DI	- Digital Innovation
DM	- Digital Maturity
DMDC	- Digital Maturity-Digital Competencies
DMDV	- Digital Maturity-Digital Value Creation
DMDS	- Digital Maturity-Digital Security
4IR	- Fourth Industrial Revolution
FMCG	- Fast Moving and Consumer Goods
GDP	- Gross Domestic Product
GIBS	- Gordon Institute of Business School
HTMT	- Heterotrait-Monotrait
IoT	- Internet of Things
KMO	- Kaiser-Meyer-Olkin
M	- Mean
MC	- My Company
Md	- Median
MSE	- Micro and Small Enterprises
PCA	- Principal Component Analysis

R^2 - Squared Multiple Correlations

RBV - Resource-based view

RMSEA - Root Mean Square Error of Approximation

SA - South Africa

SC - Supply Chain

SD - Standard deviation

SCM - Supply Chain Management

SC - Standard Deviation

SEM - Structural Equation Modelling

SCR - Supply Chain Resilience

SCR-FS - Supply Chain Resilience-Financial Strength

SCR-MD - Supply Chain Resilience-Market Diversification

SCR-OA - Supply Chain Resilience-Operational Agility

SCR-RA - Supply Chain Resilience-Resource Agility

SCR-RDM - Supply Chain Resilience-Responsive Demand Management

SCR-RF - Supply Chain Resilience-Resource Flexibility

SCR-RM - Supply Chain Resilience-Risk Mitigation

SCR-SCC - Supply Chain Resilience-Supply Chain Coordination

SCR-SCF - Supply Chain Resilience-Supply Chain Flexibility

SME - Small and Medium Enterprises

SPSS - Statistical Package for Social Sciences

SRMR - Standardised Root Mean Square Residual

VUCA - Vulnerable, Uncertain, Complex and Ambiguous

χ^2 - Chi-square

CHAPTER 1 – INTRODUCTION TO RESEARCH PROBLEM

1.1 Research introduction

This chapter outlines the research study's background and discusses its relevance to the business fraternity and academia. Furthermore, it discusses the problem and purpose statement, objectives and significance of the study, scope and methodological limitations, and the research report layout.

1.2 Research background

1.2.1 Digital technologies and Industry 4.0

Digital technologies offer companies a new way to derive value and increase competitiveness sustainably, leading to business digitisation across many industries and sectors (Martínez-Caro et al., 2020). Business digitisation refers to an organisation’s approach and ability to exploit new digital technologies in its business processes to derive value for its stakeholders (Martínez-Caro et al., 2020). The manufacturing industry is currently being dominated by Industry 4.0, also known as the Fourth Industrial Revolution (4IR) which entails the use of digital technologies such as automation, robotics, big-data, artificial intelligence, and the Internet of Things (IoT) to improve efficiency, productivity and profitability of manufacturing operations (Felsberger et al., 2022; Pozzi et al., 2023).

High wage costs in developed countries drove manufacturing automation as population growth increased demand, and developed markets struggled to compete with low-cost production countries (Iftikhar et al., 2024). IoT provides real-time monitoring by connecting devices and sensors that collect and exchange data, which is used to improve productivity through predictive maintenance and enhance customer experience (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023). IoT can predict a machine failure before it occurs, thereby optimising the frequency and timing of preventative maintenance and reducing production downtime from unplanned breakdowns and corrective maintenance (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023).

Big data analytics analyses large and complex datasets to enable organisations to gain helpful insight for improved decision-making throughout their supply chain, driving organisational success and competitive advantage (Felsberger et al., 2022;

Iftikhar et al., 2024; Pozzi et al., 2023). Big data can also be used to understand product consumption patterns to ensure more accurate demand forecasting, which in turn informs production plans and raw materials procurement (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023).

Artificial intelligence is the simulation of machines with human intelligence that performs learning, problem-solving, and decision-making (Aly, 2020). Robotics and machine learning in a manufacturing environment allows production data to be learned and adapted, improving production efficiencies and reducing costs (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023). This is smart manufacturing and can enhance warehouse, transportation, and inventory management (Del Giudice et al., 2021). This improves productivity and enhances customer experience due to more consistent, higher-quality, and reliable production output (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023).

1.2.2 Critical success factors of Industry 4.0

Limited studies have been done on the critical success factors of Industry 4.0 in manufacturing companies (Pozzi et al., 2023). Tortorella et al. (2022) conducted a study that revealed no correlation between the success of Industry 4.0 initiatives and the specific manufacturing strategy an organisation employs. However, the study did find that an organisation's readiness for Industry 4.0 significantly influenced its success in implementing these initiatives. Pozzi et al. (2023) found that the critical success factors for Industry 4.0 implementation in manufacturing organisations include leadership support, quality and flexibility-based competition as well as Industry 4.0 readiness in terms of skills, training and establishing cross-functional teams. A meta-analysis by Sahoo et al. (2022) on the critical success factors of Industry 4.0 implementation in the manufacturing industry included leadership support, training and development, innovation capabilities, culture, change management, cybersecurity, resources and standardisation of processes. The above critical success factors can be categorised into technological readiness, organisational capabilities and strategic alignment.

Based on studies conducted in the literature, a common critical success factor is an organisation's digital maturity, which speaks to technological readiness, organisational capabilities, and strategic alignment of digitalisation (Teichert, 2019).

Digital maturity refers to an organisation's readiness and capabilities to exploit digital technologies to create value for its shareholders (Gökalp & Martinez, 2022).

1.2.3 Emerging markets and digital maturity

Organisations in emerging markets have been lagging when it comes to digital maturity due to the high cost of implementation involved, and those that have made the investments tend to be more resilient during times of crisis (Kohli & Melville, 2019). Studies have shown a reciprocal relationship between digital maturity and digital innovation on a firm's performance and competitiveness (Kohli & Melville, 2019; Zhao et al., 2023). There is increasing competition globally with organisations in various industries looking to stay competitive to keep and grow market share in a constantly evolving and uncertain business environment, the fast-moving consumer goods (FMCG) industry is no exception to this (Niedermeier et al., 2021).

There is growing pressure globally for manufacturing organisations to reduce pollution. However, emerging markets like South Africa now face paired objectives of driving economic growth and climate change (Ngepah et al., 2024). This makes the case for fast-tracking digital transformation in emerging markets even more critical. Industry 4.0 aids organisations in achieving industrial performance, which gives organisations a competitive advantage (Kohli & Melville, 2019). While developed countries enjoy the benefits of Industry 4.0, with some transitioning to Industry 5.0 (Mourtzis et al., 2022), emerging markets face a challenge from the low maturity of previous industrial stages (Kohli & Melville, 2019; Shakur et al.,2024). A study in the Brazilian industries found that while some organisations invested in software acquisition, they did so simply to automate their operations (Dalenogare et al., 2018). These organisations lacked digital innovation to extract value from advanced tools that would give them a competitive advantage. Organisations in emerging markets tend to be late adopters as low cost is the main driver for competitive advantage and not necessarily differentiation (Shakur et al.,2024).

Emerging markets' lack of digital maturity was evident during the COVID-19 global pandemic, as they could not fully exploit digital technologies' benefits in mitigating supply chain disruptions (Mishrif & Khan, 2023).

1.2.4 Consequences from lack of adoption in previous industrial stages

During Industry 1.0, businesses that did not mechanise using resources like water, steam, and fossil fuels failed to scale (Putra & Muslim, 2024; Raschke, 2022; Verma, 2024). Small-scale artisans who failed to adapt could not compete with more giant manufacturers, for example, in the textile industry (Orisadare et al., 2024).

The age of electrification, termed Industry 2.0, allowed for assembly lines, which further favoured mass production (Putra & Muslim, 2024; Raschke, 2022; Verma, 2024). This led to the dominance of the *Ford Motor Company* as it used mass production to take competitors like *Studebaker* out of the market (Putra & Muslim, 2024; Raschke, 2022; Verma, 2024).

The third industrial revolution led to a rise in the automation of production lines due to a shift towards computer technology and software (Putra & Muslim, 2024; Raschke, 2022; Verma, 2024). Organisations such as International Business Machines (IBM) Corporation successfully transitioned from hardware manufacturing to software, taking advantage of the digital age (Rahman et al., 2022a). Organisations such as Xerox failed to shift to the digital age, losing market share to the likes of Apple (Wu et al., 2017). Industry 4.0 saw IoT, artificial intelligence, and cloud computing dominate the past decade, but adoption is still lacking in emerging markets (Putra & Muslim, 2024; Raschke, 2022; Verma, 2024).

As developed markets transition into Industry 5.0, the lack of adoption of Industry 4.0 should be a serious concern (Mourtzis et al., 2022). History has shown that organisations that fail to adopt tend to lose market share. Geographical distances between developed and emerging markets have protected local organisations from competition (Di Paola et al., 2023). However, as the world is increasingly interconnected, so are the global supply chains (Ali et al., 2021; Jermsittiparsert, 2022; Ponomarenko & Rasshyvalov, 2023). It is now a transformation imperative for organisations in emerging markets to embrace digitisation and improve their digital maturity and innovation. This is the only way they continue to compete, sustain and grow market share.

1.2.5 The nature of the FMCG industry in South Africa

The nature of the FMCG industry is a high-volume and low-margin business; therefore, staying competitive and resilient through disturbances is vital to the profitability and long-term survival of organisations in this industry (Niedermeier et al., 2021). Supply chain resilience (SCR) is the ability of a supply chain to adapt and persist through disturbances such that the impact on cost, revenue and its customer base is minimised (Dubey et al., 2019; Zhao et al., 2023). SCR enhances the competitiveness of an organisation and drives performance (Gölgeci et al., 2023). Given its nature, SCR is necessary in the context of the FMCG industry.

South Africa (SA) is Africa's leading manufacturing hub (Atiase et al., 2020), and the FMCG industry contributed 20% to SA's gross domestic product (GDP) in the year 2021-2022 (Statistics South Africa, 2022). The FMCG industry is, therefore, one of the most important industries that affect the economic outlook of South Africa. Digital technologies assisted organisations in developed countries such as Germany, Sweden and Poland to operate efficiently during the Covid-19 pandemic (Mishrif & Khan, 2023). The impact of digitisation on SCR in emerging markets is not fully understood (Ghobakhloo et al., 2023).

1.3 Theoretical relevance of the study (gaps in the literature)

According to the literature, digital maturity positively influences digital innovation, which positively influences supply chain resilience (Del Giudice et al. (2021; Zourari et al., 2021). The dynamic capabilities and resource-based view theories are widely accepted as frameworks of choice in strategic management and organisational studies (Ferreira et al., 2022; Gupta et al., 2020). They correctly characterise the need for industries to adopt digital technologies (resources) that will allow them to adapt and respond to market changes through innovation to maintain a competitive advantage (Ferreira et al., 2022; Gupta et al., 2020). The views expressed in the literature are logical when using these theories to explain the relationship between digital maturity, digital innovation, and supply chain resilience. A direct relationship between digital maturity and supply chain resilience is also supported in the literature. However, limited literature exists on these relationships in an emerging market context (Weerabahu et al., 2023).

Furthermore, the previous studies were not conducted exclusively within a dynamic industry such as the FMCG industry. Studies conducted in emerging markets also involved small and medium enterprises (Robertson et al., 2022), which begs the question of whether company size played a role in the findings of those studies. There is also no consensus in the literature on the most critical dimensions of supply chain resilience (Han et al., 2020; Li et al., 2017; Rahman et al., 2022b).

This study theoretically aims to understand the relationship between digital maturity, digital innovation, and supply chain resilience. It contributes to the literature by giving a perspective from an emerging market, South Africa, and suggesting the most critical dimensions of supply chain resilience in this context. Furthermore, the study aims to shed light on the impact of the dynamic nature of the FMCG industry and company size on these relationships.

1.4 Business relevance of the study

The business world is rapidly evolving with organisations faced with opportunities and threats that will affect their continued survival unless they are strategically agile (Elali, 2021). Today's business environment is vulnerable, uncertain, complex, and ambiguous, requiring organisations to focus on building capabilities that allow for strategic agility (Haarhaus & Liening, 2020). Organisations that have endured longevity suggest that the firms recognised and seized the opportunities that digitisation presents (Rossato & Castellani, 2020).

This is especially important for organisations in an emerging market context like South Africa, which still lags in digital maturity and innovation (Magagula et al., 2020). To compete and thrive in an increasingly globally connected world (Ali et al., 2021; Jermsittiparsert, 2022; Ponomarenko & Rasshyvalov, 2023), organisations need to fully grasp whether digital maturity is sufficient to realise supply chain resilience in the absence of digital innovation. Furthermore, small enterprises need to understand the implications of scaling their operations on the mediation role of digital innovation on digital maturity and supply chain resilience in larger enterprises.

Organisations operating in a dynamic industry such as the FMCG industry must also be aware of the increased need for digital innovation to stay competitive (Magagula et al., 2020; Ponomarenko & Rasshyvalov, 2023).

1.5 Purpose statement

The purpose of the research study is to evaluate the impact of the use of digital technologies by South African FMCG manufacturing companies on their ability to deal with supply chain disturbances. By conducting a quantitative study through an online survey, the study aims to understand the impact of digital maturity levels and digital innovation of FMCG manufacturing companies on their SCR in the face of the uncertain business environment. This research work will contribute to the growing body of knowledge on the digitisation of manufacturing as well as the opportunities and challenges it presents to SCR in a South African FMCG context.

1.6 Statement of the problem and research questions

The digitisation of businesses can yield a competitive advantage for organisations that take advantage of Industry 4.0 technologies. Although limited studies are done to understand the critical success factors, a common factor across various studies is the organisation's state of readiness, called digital maturity. Digital maturity comes at a significant cost of implementation, leading to organisations in emerging markets lagging on digital maturity levels. Digital maturity has a reciprocal relationship with digital innovation on an organisation's performance and its ability to compete. The FMCG sector is unique because it is a highly competitive high-volume, low-profit margin industry influenced by the constantly evolving environment and consumer trends. In the context of South Africa, it contributes about 20% to the GDP. The constantly evolving global environment requires an organisation's supply chains to be resilient and studies done in developed countries have shown that digitisation can positively affect the SCR of organisations leading to firm performance.

The research problem here is to understand the impact of digital maturity and digital innovation on the SCR of the FMCG industry in the context of South Africa, an emerging market. Consequently, this research aims to answer the following two questions:

First research question: How do organisations with varying degrees of digital maturity fare in terms of supply chain resilience?

Second research question: Does digital innovation have a mediation role in the relationship between digital maturity and SCR?

1.7 Objectives of the study

This research study aims to understand the relationship between digital maturity, digital innovation and SCR in the context of the South African FMCG industry. The study measured the digital maturity level in various organisations in the FMCG industry and evaluated the relationship between digital maturity and digital innovation. Furthermore, the study assessed the relationship between digital innovation and SCR. The mediation effect of digital innovation on digital maturity and SCR was also evaluated. The study of these relationships in the context of South

African FMCG organisations was meant to fill the gap that exists in literature giving scholars a better understanding of the extent to which digital capabilities have been exploited in emerging markets to advance firm performance.

1.8 Significance of the study

This research work is significant as it will allow organisations in the FMCG industry in emerging markets such as South Africa to understand how digital maturity impacts digital innovation and SCR. This is very important given today's business environment's volatile, uncertain, complex and ambiguous nature (Jermsittiparsert, 2022). Business leaders and managers can then make decisions to prioritise company resources towards business digitisation and keeping up to date with the latest technological advancements in digital transformation to achieve sustainable organisational performance.

Additionally, reliable and resilient supply chains will ensure the economic prosperity of the countries in which these organisations operate. In South Africa, FMCG contributes around 20% to the GDP (Statistics South Africa, 2022). Therefore, understanding how SCR can be achieved through the digitisation of FMCG organisations is important for the economic stability and growth of South Africa. This will assist government and policymakers in driving initiatives that enhance digital transformation through incentives and the state’s infrastructure investments. The research study will also assist in the achievement of sustainable development goals, as the digital transformation of supply chains can contribute positively to environmental sustainability (Ngepah et al., 2024).

1.9 Scope and Limitations

This study was biased towards large enterprises in the FMCG industry in South Africa, as 76% of the respondents were from large enterprises. Further research will need to be conducted to confirm the applicability of the results of this study to other emerging markets and industry types with a more significant representation of smaller enterprises. The target sample size for this study was also minimised based on resource constraints, potentially compromising the sample representativeness of the population. However, care was taken to ensure the minimum sample size defined by previous studies and best practices were met. The study’s findings were also limited to the views of the supply chain professionals and engaging other human resources in the organisation may yield different results. However, they are the right audience to study with.

1.10 Research Proposal Layout

Chapter 1 of this research study introduces the topic, gives background to the research problem and defines the research purpose and objectives. The study's scope, significance, assumptions, and limitations are also covered in the same section. Chapter 2 of this research study is a literature review of the main themes of this study, including digital maturity, digital innovation, SCR, and the FMCG sector, to understand what has previously been covered in the literature regarding these.

Chapter 3 outlines the study’s conceptual model and the hypothesis and research questions the study intends to address. The theoretical foundation that grounds this study is also outlined in this section. Chapter 4 of this research study covers and defends the research design and methodology utilised to answer the research questions that address the problem identified in Chapter 1. The pilot study undertaken and the data collection and analysis procedures followed are also outlined in this section. The quality controls and ethical considerations resulting from employing the chosen research methodology are also covered, and the study's limitations are also covered in Chapter 4.

Chapter 5 outlines the study's results, confirming the reliability and validity of the constructs of interest. The study's findings are summarised, and Chapter 6 discusses the results and draws conclusions based on them. Chapter 7 covers the main findings that can be concluded from the study and their implications. Recommendations are then made based on the main findings and study implications for the business community. Areas of future study are identified for scholars to build on this work.

CHAPTER 2 – LITERATURE REVIEW

2.1 Introduction

The literature review section of this research proposal explores the main themes of this study which include, digital maturity, digital innovation and SCR. The nature of the FMCG sector in an emerging market context is also explored to understand what has previously been covered in the literature. The relationship between digital maturity, digital innovation and SCR is explored in the literature to identify gaps and introduce hypotheses that aim to answer the research questions.

2.2 Understanding Digital Maturity, Digital Innovation and SCR

2.2.1 What is Digital Maturity?

The term maturity refers to the capability of an organisation to react to the environment appropriately with management practices (Thordsen et al., 2020; Wagire et al., 2021). Although the reaction to the environment is not instinctive but rather learned through practice, maturity in this context does not always relate to the age of the organisation (Thordsen et al., 2020). It is widely accepted that higher maturity levels allow organisations to achieve organisational performance (Eichholz et al., 2023; Fletcher & Griffiths, 2020). Digital maturity can be defined as an organisation's capabilities to exploit digital capabilities to achieve organisational performance (Thordsen et al., 2020; Wagire et al., 2021). Critical evaluation of digital maturity models indicates that most models lack generalisability and consistency (Teichert, 2019; Thordsen et al., 2020). This implies that further research on the digital maturity construct is required to address this in the literature.

2.2.2 What is Digital Innovation and its relation to Digital Maturity?

Digitally maturing organisations have better innovation capabilities enhanced by collaborative efforts through digital ecosystems and internal cross-functional teams (Kane et al., 2019). Digital Innovation refers to the adoption, generating or recombining of digital technologies to generate value and adapt their business models to fit the constantly evolving and uncertain environment (Felicetti et al., 2024). Digital Innovation allows for the interface between digital technologies and human resources to aid the transfer of knowledge and information with the assumption that the knowledge will serve as an engine of profit generation (Di Vaio et al., 2021). Therefore, it can be inferred that digital innovation enhances organisations' knowledge management systems, providing them a competitive edge over their counterparts. Knowledge management systems are a key driver in achieving SCR during times of disruption (Chen et al., 2024; Ali et al., 2021), and this disruption can be driven by external factors such as a global pandemic or advancement in digital technologies (Ali et al., 2021).

It can thus be implied that digital maturity is the foundation for digital innovation. Organisations that boast of digital infrastructures, and digital competence, and have embedded a digital culture have a competitive advantage to continuously innovate. Digitally mature organisations have the tools, processes and people capabilities to continuously drive digital innovation. Consequently, it seems there exists a feedback loop whereby digital innovation improves digital maturity by introducing new technologies that are accessible and valuable for organisations to integrate into their operations. This in turn fosters more digital innovation.

2.2.3 What is SCR and its relation to Digital Innovation?

According to the work of the scholar Holling on the Resilience theory, two types of resilience exist: engineering resilience and social-ecological resilience (Revilla et al., 2024; Wieland & Durach, 2021). Engineering resilience refers to the ability of a system to return to its original form after a disturbance (Revilla et al., 2024; Wieland & Durach, 2021), and ecological resilience is resilience not only in terms of stability but also in considering how adaptive and transformative the system is (Revilla et al., 2024; Wieland & Durach, 2021). Ecological resilience is focused on persistence and is defined as the amount of disturbance that a system can handle before the system control or structure is affected (Revilla et al., 2024; Wieland & Durach, 2021). The ecological resilience interpretation is not widely used when it comes to supply chain management (Revilla et al., 2024; Wieland & Durach, 2021). The engineering interpretation is an oversimplification of supply chain disturbances organisations face (Wieland & Durach, 2021).

Today's business environment is complex, uncertain, non-linear and unambiguous (Di Paola et al., 2023), much like the social-ecological system (Revilla et al., 2024; Wieland & Durach, 2021). In recent literature, there is a prominent view of the definition of SCR as the capacity of a supply chain to show persistence, adaptability, or transformative capability when faced with a disruption or change (Wieland & Durach, 2021).

Because digital innovation allows the organisation to adapt their business models through the adoption, generation or recombination of digital technologies (Felicetti et al., 2024), it satisfies the SCR definition of the capacity to be adaptive. Additionally, digital innovation can disrupt organisations and industries influencing organisational decision-making and capabilities, which when possessed aids the transformative capacity of organisations (Ghosh et al., 2022).

Digital innovation enhances knowledge management systems to drive information flow and visibility through data analytical tools communication assistance, knowledge transfer and proactive risk management practices (Di Vaio et al., 2021). This relationship allows digitally mature organisations to be more persistent to disruptions as they are equipped to continuously and proactively manage risk (Mukherjee et al., 2024). Consequently, it can be inferred that digital innovation enhances the capabilities that are necessary ingredients in resilient supply chains aligned with the prominent definition of SCR emanating from ecological resilience.

2.3 Impact of Digital Maturity on SCR

Due to recent events of pandemics, geo-political instability and natural disasters, organisations are looking at allocating resources towards making their supply chain more resilient (Dubey et al., 2023; Tortora et al., 2021). Digital adaptation leads to digital agility and has a positive and significant impact on SCR (Dubey et al., 2023). Digital adaptation refers to the ability of the organisation to respond to changes in the digital environment (Tortora et al., 2021). Digital maturity can be characterised as the baseline of digital transformation, and it is concerned with integrating organisational resources and processes into the digital processes (Aslanova & Kulichkina, 2020).

Consequently, digital maturity is a precursor to digital adaptation as an organisation cannot adapt to changes in the digital environment if it is not or has not undergone the integration of organisational resources and processes with digital processes. This suggests that there may be a relationship between digital maturity and SCR. Furthermore, to exploit digital innovation for competitiveness digital maturity is a building block of this capability (Kohli & Melville, 2019). This implies that there is a relationship between digital maturity and digital innovation. The following hypotheses are thus proposed:

Hypothesis 1: Digital maturity positively impacts digital innovation.

There is limited literature on understanding the relationship between digitisation and the supply chain's capabilities in different geographical contexts and industries (Weerabahu et al., 2023). We, therefore, need to understand if digital maturity leads to digital innovation and what impact this has on SCR in emerging markets such as South Africa.

Emerging markets provide growth opportunities but are also characterised by high risk from global and local factors (Aly, 2020). This creates a competitive environment for organisations that then need to balance managing risk and exploiting growth opportunities (Aly, 2020).

2.4 The influence of Digital Maturity on Digital Innovation

Organisations cannot successfully realise sustainable digital innovation unless they are digitally mature enough to exploit the digital technologies in a manner that will create more value for the business (Kohli & Melville, 2019). Digital innovation allows organisations to be able to renew and change their business models to stay competitive in response to the business environment they face (Ancillai et al., 2023; Kohli & Melville, 2019). Because digital innovation drives organisational competitiveness and performance, it is proposed that the following relationship exists:

Hypothesis 2: Digital innovation has a positive influence on SCR.

The strength of the influence of the digitalisation of supply chain enablers on business competitiveness depends on the digital maturity of the firm (Zheng et al., 2021). Therefore, the direction of the digital adoption strategy should be based on the digital maturity of the firm. Digital innovation cannot be achieved unless an organisation has a digital adoption strategy that enhances and leverages its digital maturity (Kohli & Melville, 2019). This suggests that for organisations to stay competitive they must work on their digital maturity and use it to modify and adapt their digital adoption strategies to realise digital innovation.

2.5 Digital Innovation as a Mediator between Digital Maturity and SCR

The use of innovative technologies, also known as digital innovation, drives data analytics, allowing organisations to predict and reduce the impact of disruptions while ensuring organisational survival (Iftikhar et al., 2024). The level of digitisation is not directly linked to SCR, but it mediates the relationship between Supply Chain

Integration and SCR (Shi et al., 2023). Digital maturity refers to the extent of digital technology adoption and how well they are used and integrated into an organisation's processes, culture and strategic focus (Thordsen et al., 2020; Wagire et al., 2021). This means that it cannot be assumed that digital maturity is also not directly linked to SCR. Supply chain disruptions such as the COVID-19 pandemic allow innovation in organisations to foster workforce resilience for organisational survival (Ambrogio et al., 2022). A study done on port firms in China found that technological innovation positively mediates the relationship between digital transformation and SCR (He et al., 2023). Because digital transformation requires digital maturity for it to be effective (Mugge et al., 2020), then the following hypothesis is also proposed:

Hypothesis 3: The relationship between digital maturity and SCR is mediated by digital innovation.

2.6 The role of digital maturity in emerging and developed markets

Digital maturity has been key in driving economic growth and reconfiguring business models (Ngepah et al., 2024). It is a common cause that the digital maturity levels differ between emerging and developed markets. The impact also differs significantly (Dalenogare et al., 2018; Mishrif & Khan, 2023); organisations must understand these variations to ensure a successful digital transformation journey (Ngepah et al., 2024). The impact differs due to the availability and accessibility of digital infrastructure, the country's economic context, market dynamics, and organisational factors (Shakur et al.,2024).

2.6.1 Availability and accessibility of digital infrastructure

Organisations in developed markets generally benefit from extensive digital infrastructure and technological ecosystems (Mishrif & Khan, 2023). This allows them to leverage digital technologies more efficiently, driving high levels of digital maturity (Kohli & Melville, 2019). These organisations can then invest in advanced and emerging digital technologies, allowing continuous innovation and improving operational efficiencies (Mishrif & Khan, 2023). On the contrary, those in emerging markets are often constrained by inadequate digital infrastructure and a lack of internet access and digital skills (Dalenogare et al., 2018; Ngepah et al., 2024). Consequently, while opportunities for digital technology adoption are in abundance, organisations in these markets tend to struggle to reach the digital maturity levels often seen in developed markets (Dalenogare et al., 2018; Ngepah et al., 2024). This is a problem for multinationals who operate in both these markets, as their digital transformation strategy deployed in developed markets may fail when extended to emerging markets.

2.6.2 Market dynamics and economic context

An organisation's economic context and market dynamics are exposed to affect the impact of digital maturity (Dalenogare et al., 2018; Mishrif & Khan, 2023; Ngepah et al., 2024). In developed markets, organisations tend to operate in competitive environments where digital transformation is critical for sustaining and growing market share (Mishrif & Khan, 2023). Digital maturity allows differentiation in these markets, driving innovation to enhance customer experience (Shakur et al.,2024). The type of industry is also crucial as industries such as the FMCG industry are characterised by high levels of competition (Niedermeier et al., 2021). Conversely, in emerging markets, organisations can be presented with unique opportunities, especially in mobile applications that do not necessarily need comprehensive infrastructure development compared to technologies like artificial intelligence (Aly, 2020). This is key as consumers in these markets are typically price-sensitive (Shakur et al.,2024). Organisations in emerging markets must ensure their digital maturity levels allow for rapid adoption of digital solutions to gain a competitive edge (Van den Born et al., 2020; Humaidi et al., 2023). Innovation is critical in emerging markets as organisations typically implement well-established digital technologies. They need to be able to do it differently and as quickly as possible to gain a competitive edge.

2.6.3 Organisational factors

Due to higher levels of digital maturity and better adoption in previous industrial stages, developed markets tend to have a better culture of digital innovation (Mourtzis et al., 2022). This drives the appetite to invest in digital technologies. In contrast, there is poor adoption in previous industrial stages and relatively lower digital maturity levels in emerging markets (Putra & Muslim, 2024; Raschke, 2022; Verma, 2024). Consequently, organisations in these markets face cultural resistance and a lack of awareness of the value that could be derived from digital technologies (Shakur et al.,2024). This makes the digital transformation journey more challenging in emerging markets, though there is significant potential for growth (Shakur et al.,2024; Telukdarie et al., 2023). The need to be innovative is thus crucial in an emerging market context to fully capture the growth potential in these markets while maintaining a low cost (Aly, 2020).

Digital maturity is essential for organisational success in developed and emerging markets. However, the roadmap and challenges differ, which requires organisations to tailor their digital strategies according to their respective market conditions and opportunities.

2.7 Industry 4.0 and SCR in FMCG organisations in emerging markets

2.7.1 FMCG companies in emerging markets

FMCG are typically low-margin, high volume sold fast and have limited shelf life (George & George, 2023; Niedermeier et al., 2021). FMCG examples are beverages, toiletries, cleaning products, packaged food and over-the-counter medication (Ermes et al., 2022). The FMCG industry is characterised by high competition with a need to compete on price while building brand loyalty through investment in marketing and product quality to defend and grow market share (Eltawy et al., 2021). The FMCG industry outlook mirrors consumers' disposable income and hence the country's economic performance (Wilkins & Ireland, 2022).

Additionally, the FMCG business environment is volatile, uncertain, complex and ambiguous as it is affected by external factors such as pandemics and geopolitical issues such as the Russia/Ukraine war (Ponomarenko & Rasshyvalov, 2023). Although emerging markets offer higher growth potential, they are more susceptible to disruption by both global and local factors (Aly, 2020). Consequently, the complex nature of the FMCG industry in emerging markets necessitates implementing measures to ensure market survival.

Most consumers of goods in emerging markets are looking for low-cost and highest-possible quality products that meet their needs (Arunachalam et al., 2020). Industry 4.0 provides FMCG organisations with viable technologies to improve process efficiency and product quality at the lowest cost possible, thus staying competitive (Shakur et al., 2024). The most significant barriers to implementing the digitalisation of the FMCG supply chain in emerging markets are the high cost of investment and resources and a lack of compatible technological infrastructure (Shakur et al.,2024). Tackling these barriers requires organisational leaders in emerging markets to take risks to position their companies to exploit the opportunities presented by Industry 4.0 in rendering their supply chains resilient.

2.7.2 The importance of Industry 4.0 in the FMCG industry

Industry 4.0 technologies that the FMCG industry can exploit include automation, robotics, big data, artificial intelligence and the Internet of Things (IoT) to improve the efficiency, productivity and profitability of manufacturing operations (Felsberger et al., 2022; Pozzi et al., 2023).

Automating processes allows production, logistics, customer service and sales processes to be executed faster and more precisely (Iftikhar et al., 2024). Faster and more precise execution of processes will ensure more rapid recovery from any supply chain disruption, minimising the disruption's impact and enhancing the supply chain's resilience. Big data allows for predictive analytics which can be used to pre-empt disruptions and their impact (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023), this can allow organisations to adapt or embark on a transformative imperative in response to the disruption timeously and more effectively.

The IoT can assist in supply chain management by integrating the supply chain to improve visibility, decision making and efficiency through the use of sensors, software and devices (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023). IoT allows for real-time tracking of crucial process parameters in a production environment, allowing for quicker reaction to deviations and ensuring that quality control and equipment reliability are realised, it can also be used to optimise inventory as well as the route to market (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023). These would then assist in cost reduction and product quality which are essential for competitiveness in the FMCG industry in emerging markets such as South Africa.

The real-time insights made possible by IoT enable supply chains to be more persistent to disruptions and to quickly adapt and transform due to the improved supply chain visibility (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023). It is evident that the Industry 4.0 technologies offer significant benefits to supply chain management which can enhance its resilience, in the context of FMCG and emerging markets this is important to stay competitive and manage risks.

2.7.3 FMCG industry challenges in South Africa

The FMCG industry in South Africa is highly saturated and dominated by a few major players, making it highly competitive (Magagula et al., 2020). South Africa’s economic growth has been below 2% for the past decade, which is a challenge for the FMCG industry, whose performance also indicates the country's economic performance (Magagula et al., 2020). Rising unemployment figures and slow economic affect consumer spending power and purchasing behaviour as consumers gravitate towards affordable products (Francis et al., 2020). In a highly saturated industry, FMCG companies in South Africa face a challenging and complex environment where they must meet consumer needs at the lowest cost possible.

The rise of e-commerce has seen a growing trend in online retail shopping, accelerated by the COVID-19 pandemic (Elia et al., 2021).). Competition from online platforms has challenged traditional retailers with a vast network of brick-and-mortar stores to invest in digital and logistic capabilities (Elia et al., 2021). The manufacturing industry is also challenged with sustainability issues, driven by environmentally conscious consumers (Ngepah et al., 2024). South Africa has recently committed to transitioning from using coal for energy to other renewable energy sources (Cole et al., 2023). Consequently, given the government's position on climate change matters, FMCG manufacturing companies in South Africa can anticipate policies such as carbon tax to be imposed on the manufacturing industry. This challenges the FMCG industry as the initial cost of the transition towards clean energy is not cheap (Glenk et al., 2021) and may affect short-term profits in an emerging market like South Africa with price-sensitive consumers.

2.8 Digital adoption and innovation: Impact of company size

SMEs differ from larger enterprises in digital adoption and innovation due to differences in resources and organisational structure (Andersen et al., 2022)

2.8.1 Resource availability

Large enterprises tend to have more financial and human resources to invest in digital tools, infrastructure, and innovative initiatives (Müller et al., 2021). Digital skills are one of the challenges organisations with low digital maturity face (James, 2021). Large enterprises can hire and retain top talent to support in-house innovation. In contrast, smaller enterprises like SMEs are typically resource-constrained, making it challenging to adopt emerging digital technologies (Müller et al., 2021). This challenge requires SMEs to be creative and innovative to leverage well-established, cost-effective digital technologies (Andersen et al., 2022).

2.8.2 Organisational structure

Large enterprises typically have a bureaucratic organisational structure that can slow decision-making (Müller et al., 2021). This can hamper rapid innovation and the implementation of digital solutions. Conversely, SMEs have leaner organisational structures that allow faster decision-making and improved agility to respond to market conditions (Andersen et al., 2022). While this may support rapid innovation, the lack of formal processes may disadvantage SMEs in achieving and sustaining long-term innovation (Müller et al., 2021). Larger enterprises tend to be better at long-term innovation (Andersen et al., 2022).

2.9 Gaps in the Literature

During the COVID-19 pandemic, digital technologies in emerging markets like India were less widespread than in developed markets like China (Gupta et al., 2022). Consequently, organisations in developed nations experienced better SCR due to digital capabilities (Gupta et al., 2022). The barriers to implementing digital technologies in emerging markets include the high cost of implementation, inadequate infrastructure and lack of clarity on the return on digital investment (Gupta et al., 2022; Paul et al., 2020).

There is limited literature on understanding the relationship between digitisation and the supply chain's capabilities in different geographical contexts and industries (Weerabahu et al., 2023). Given that South Africa is an emerging market and the most industrialised country in Africa with the FMCG industry contributing about 20% to its GDP (Statistics South Africa, 2022), more studies need to be done to understand the impact of digitisation on the SCR of the FMCG industry in South Africa.

Furthermore, it has been suggested in the literature that one of the building blocks of digital innovation capability is digital maturity (Kane et al., 2019). However, It is unclear if this relationship applies to an emerging market like South Africa and the FMCG industry. It has also been established in the literature that digital innovation leads to organisational competitiveness (Ancillai et al., 2023; Kohli & Melville, 2019) but it is not clear if this means that digital innovation positively influences an organisation’s SCR. Previous studies have also found that technological innovation mediates the relationship between digital transformation and SCR (He et al., 2023) and that digital maturity allows for successful digital transformation (Thordsen et al., 2020). It is, however, not clear whether digital innovation mediates the relationship between digital maturity and SCR.

We, therefore, need to understand if digital maturity leads to digital innovation and what impact this has on SCR in the context of emerging markets such as South Africa in the FMCG industry. Consequently, the proposed hypothesis for this study is summarised as follows:

Hypothesis 1: Digital maturity positively impacts digital innovation.

Hypothesis 2: Digital innovation has a positive influence on SCR.

Hypothesis 3: The relationship between digital maturity and SCR is mediated by digital innovation.

2.8 Conclusion

The impact of digital maturity and digital innovation on SCR in the context of the FMCG industry in South Africa, an emerging market is not fully understood. Organisations in developed countries benefited from the use of digital technologies during the COVID-19 pandemic, minimising the impact of the pandemic on the supply chains of organisations in those markets.

Organisations in emerging markets have been lagging in terms of digital maturity. The barriers to digitisation in emerging markets are attributed to a lack of funding and infrastructure as well as an understanding of the benefit that digitisation could yield. Investing in digitisation and a focus on digital adoption and capabilities as well as digital integration leads to digital maturity. This research study aims to answer the research questions about the relationship between digital maturity and digital innovation, and how this relationship influences SCR. Furthermore, it aims to answer the question if digital innovation has a mediation role in the relationship between digital maturity and SCR.

Organisations in emerging markets do not enjoy the benefits of digital technologies to the same extent as those in developed countries during the COVID-19 pandemic. Consequently, they tend to be less competitive and resilient thus hindering firm performance. This study aims to close the gaps found in the literature by establishing the nature of the relationships between digital maturity, digital innovation and SCR in the FMCG industry in South Africa.

CHAPTER 3 – CONCEPTUAL MODEL AND HYPOTHESIS

3.1 Introduction

This research study seeks to close the gaps found in the literature by establishing the nature of the relationships between digital maturity, digital innovation, and supply chain resilience in the FMCG industry in South Africa, an emerging market. Additionally, the mediation effect of digital innovation on supply chain resilience is evaluated. Chapter three outlines the conceptual model and the hypotheses.

3.2 Theoretical Model Development

The theoretical foundation for the conceptual model is grounded in two theories, namely, the dynamic capabilities theory and the resource-based view (RBV) theory. The dynamic capabilities theory argues that for an organisation to sustain a competitive advantage in a dynamic environment, it needs to integrate, develop, and reconfigure its internal and external competencies (Gupta et al., 2020). In this study, digital maturity and innovation represent dynamic capabilities that enable organisations to respond rapidly and effectively to supply chain disruptions, enhancing resilience. The RBV theory stipulates that organisations can achieve sustained competitive advantage by exploiting valuable, rare and inimitable resources (Ferreira et al., 2022). Integrating digital technologies into the supply chain creates strategic assets that are not easily duplicated by competitors, fostering competitiveness and supply chain resilience.

3.3 Research Questions

The digitisation of businesses can provide a competitive edge through Industry 4.0 technologies. Limited studies have explored the critical success factors, but digital maturity is a common factor. However, the cost of implementation often hinders digital maturity, especially in emerging markets. Digital maturity significantly influences an organisation's ability to innovate and compete. The FMCG sector, contributing about 20% to South Africa's GDP, operates in a highly competitive and evolving environment. Digitisation has positively impacted supply chain resilience and firm performance in developed countries.

First research question: How do organisations with varying degrees of digital maturity fare in terms of supply chain resilience?

Second research question: Does digital innovation have a mediation role in the relationship between digital maturity and SCR?

The proposed conceptual model is represented in Figure 1a:

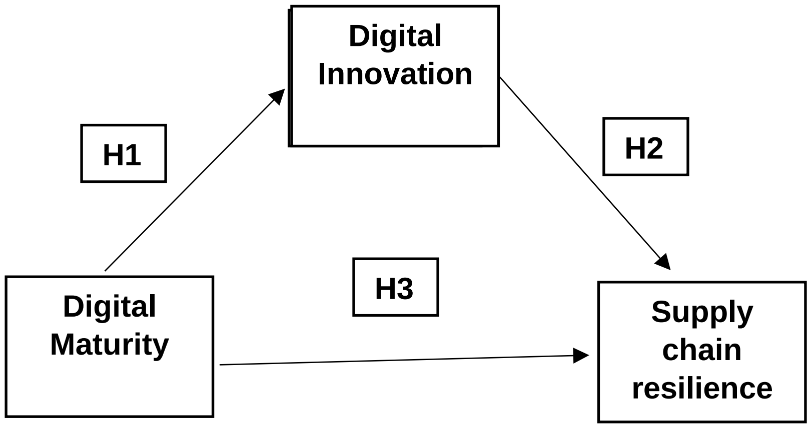

Figure 1a: Conceptual model underpinning the study's hypotheses

The theoretical model represented in Figure 1a integrates the constructs of digital maturity, digital innovation, and SCR. Digital maturity is expected to directly influence SCR, while digital innovation is hypothesised to mediate this relationship.

3.4 Hypotheses

3.4.1 Hypothesis 1

Organisations are focusing on building resilience in their supply chain due to recent pandemics, geopolitical instability, and natural disasters (Dubey et al., 2023; Tortora et al., 2021). Digital adaptation, an organisation's ability to respond to changes in the digital environment, positively impacts supply chain resilience (SCR) (Dubey et al., 2023). Digital maturity, which involves integrating organisational resources and processes into digital processes, is a precursor to digital adaptation and is linked to SCR. Additionally, digital maturity is essential for leveraging digital innovation for competitiveness (Kohli & Melville, 2019). This indicates a relationship between digital maturity, SCR, and digital innovation. The following hypothesis is thus proposed:

H1: Digital maturity positively impacts digital innovation.

3.4.2 Hypothesis 2

Organisations must be digitally mature to effectively leverage digital technologies for increased business value (Kohli & Melville, 2019). Digital innovation enables organisations to adapt their business models to remain competitive in their business environment (Ancillai et al., 2023; Kohli & Melville, 2019). As digital innovation drives organisational competitiveness and performance, it is suggested that a significant relationship exists in this context:

H2: Digital innovation has a positive influence on SCR.

3.4.3 Hypothesis 3

Digital innovation, through the use of innovative technologies, contributes to data analytics, enabling organisations to predict and mitigate disruptions' impact on organisational survival (Iftikhar et al., 2024). The digitisation level is not directly linked to supply chain resilience (SCR) but influences the relationship between supply chain integration and SCR (Shi et al., 2023). Digital maturity denotes the extent of digital technology adoption and its integration into an organisation's processes, culture, and strategic focus (Thordsen et al., 2020; Wagire et al., 2021). Organisational innovation in response to disruptions, such as the COVID-19 pandemic, enhances workforce resilience for organisational survival (Ambrogio et al., 2022). Additionally, technological innovation mediates the relationship between digital transformation and SCR, as evidenced in a study on port firms in China (He et al., 2023). Furthermore, digital transformation requires digital maturity to be effective (Mugge et al., 2020), thus supporting the proposed hypothesis.

H3: The relationship between digital maturity and SCR is mediated by digital innovation.

3.5 Conclusion

This chapter presented the theoretical research model and the hypotheses. The theoretical model allows for evaluating the impact of digital maturity and innovation on supply chain resilience in a South African FMCG industry context.

CHAPTER 4 – RESEARCH METHODOLOGY AND DESIGN

4.1 Introduction

This section introduces and justifies the research methodology employed for this study. A positivist philosophy with a cross-sectional, descriptive and mono-methodic quantitative approach was used to address the study’s objectives and scope. The study was conducted with South African FMCG industry supply chain managers. The following sections cover and defend the research design and methodology utilised to answer the research questions that address the problem identified in Chapter 1. The pilot study undertaken, as well as the data collection and data analysis procedures followed, are also outlined in this section. The quality controls and ethical considerations resulting from employing the chosen research methodology are also covered, and the study's methodological limitations are also covered.

4.2 Research Methodology

4.2.1 Research Philosophy

There exist two research philosophies which aim to interpret, understand and explain phenomena, namely positivism and interpretivism (Ugwu et al., 2021). Positivist philosophy aims to use empirical evidence gathered from quantitative methods to explain a causal relationship and is thus said to be objective as opposed to interpretivism which typically uses qualitative methods to get a deeper understanding or perspective and is thus subjective (Ugwu et al., 2021). Given that the study is concerned with understanding the relationship between digital maturity, digital innovation and SCR, a positivist philosophy was deemed more appropriate for this study.

4.2.2 Research Approach

The approach to theory development can be deductive or inductive (Okoli, 2023). A deductive approach starts with general principles and derives research questions from these principles, data is then collected to prove or reject the initial principles or theory (Okoli, 2023). An inductive approach starts with the collection of data to identify themes within the data set, and general theories are derived from the data (Okoli, 2023). Digitisation is a well-researched topic, but this study aims to understand the relationship between the three constructs of digital maturity, digital innovation and SCR in the context of the South African FMCG industry. Consequently, a deductive approach to prove or reject what existing knowledge suggests about this relationship was selected as the most appropriate approach for this study.

4.2.3 Research Design Purpose

Descriptive research aims to describe phenomena within a population of interest (Williams, 2007). Consequently, a descriptive research design was followed in this research study as it was deemed to be suitable to answer the research questions. The use of this research design allowed for the relationship between digital maturity, digital innovation and SCR to be described and understood. The outcome of the descriptive research design provided a view at a point in time which gave an understanding of the relationship in the context of the South African FMCG industry.

4.2.4 Methodological Choice

The methodological choice is made based on the research questions that need to be answered, the context as well as the available resources at the disposal of the researcher (Vivek, 2021). In this case, a monomethod approach was employed as a single quantitative research method is sufficient to understand the relationship of the variables being investigated and also due to time and resource constraints it makes sense to keep it to a single approach.

4.2.5 Research Strategy

A research strategy is selected based on the aim of the research as well as the research questions and context of the study (Johannesson et al., 2021). The literature review that guides this study suggests that digital maturity leads to digital innovation and that constructs such as digital adaptation do influence SCR. Due to the inherent relationship between digital maturity and digital adaptation, it can be inferred that there may be a relationship between digital maturity, digital innovation and SCR. Therefore, a survey research study to collect data from supply chain professionals to give insights into the relationship between the three constructs was deemed an appropriate choice.

4.2.6 Research Time Horizon

The time horizon can be cross-sectional or longitudinal, a cross-sectional time horizon collects data at a specific point and will provide a snapshot of the relationship being investigated at the present moment, a longitudinal time horizon on the other hand collects the data over some time check if the observations change over time (Wang & Cheng, 2020). Longitudinal studies tend to provide more insight into the phenomenon under study but can tend to be complex, tedious and resource-consuming (Wang & Cheng, 2020). Consequently, given the resource constraints in this study, a cross-sectional time horizon was deemed an appropriate time horizon that will give scholars and supply chain professionals insights into the current state of the relationship between digital maturity, digital innovation, and SCR in a South African FMCG industry context.

4.3 Research Design

4.3.1 Population

The selection of a population for a study is a function of the scope, research aim and methodology that is being used (Sukmawati et al., 2023). A population needs to be well-defined for the results of the study to be viewed as valid and for the findings to be applied appropriately (Sukmawati et al., 2023). In this study, the population of interest was defined as South African companies in the FMCG industry. This population was deemed appropriate as the study aimed to understand the relationship between digital maturity and digital innovation and how these affect the SCR of the organisation in the context of the South African FMCG industry. The FMCG industry in South Africa employs over 1.1 million people (Statistics South Africa, 2023).

4.3.2 Unit of Analysis

The unit of analysis is the level at which the research data collection, analysis and interpretation was conducted within the population (Sukmawati et al., 2023). It is an important aspect of the research study and depends on the research objectives, methods and scope of the study (Sukmawati et al., 2023). The unit of analysis in this study was supply chain professionals working for companies in the South African FMCG industry. The choice of the unit of analysis was appropriate as the supply chain professionals are at the centre of SCR as the human factor in the whole supply chain, they should be in a position to give insights on the relationship between an organisation's digital maturity and digital innovation, as well as the impact this has on SCR in their industry.

4.3.3 Sampling method, Sampling Size and Inclusion criteria

The sampling method chosen as well as the size must be such that it is representative of the population of interest so that the findings can be trusted and relied on (Sukmawati et al., 2023). This is important as it will give scholars and supply chain professionals confidence in the study, and they can make future decisions based on this study. Sampling method choices are dependent on the aim of the research study, the type of population of interest and resource constraints (Stratton, 2021).

Purposive sampling was chosen as the sampling method of choice for this study. Purposive sampling is a type of non-probability sampling where there is no equal chance of each sample being selected because the population is divided into specific subgroups with pre-defined characteristics (Sukmawati et al., 2023). The purposive sampling method was deemed appropriate for this study because the desired unit of analysis for the population is supply chain managers working in the South African FMCG industry; the individuals engaged in this study had to fit this pre-determined criterion. This method allows for the targeting of a specific group which are deemed relevant to the study by researchers (Sukmawati et al., 2023), in this instance a case for understanding the South African context and the FMCG industry had already been made which made this sampling method the method of choice.

Purposive sampling has the drawback of introducing bias due to the subjective selection criteria used for target sampling (Stratton, 2021), the selection criteria were based on the literature review that supports the need to focus on South Africa as an emerging market as well as on the FMCG industry in trying to understand digitisation of manufacturing. The following factors were added to the inclusion criteria to help with the validity and reliability of the results; the supply chain manager should have been working in the FMCG industry for at least five years. The study targeted supply chain managers as they were deemed to have decision-making authority when supply chain disturbances occurred. This will ensure that the insights given by the participants come from individuals who are tasked with preventing and mitigating supply chain disturbances.

There are various methods of determining the sampling size for a quantitative research study, such as sample size formulas, using previous studies as a baseline, and statistical power analysis (Rahi et al., 2019). The sample size is also influenced by the researcher's constraints, such as time, money, and human resources (Rahi et al., 2019).

A baseline sample size of such a study is estimated to be 300 participants which was determined using the previous study in the same field by Zouari et al. (2021) whereby the sample size was 300 participants with a 12.93% response rate. According to Rahi et al., there is a rule of thumb in the literature that the minimum sample size required for every 1.8 million units is about 384. The number of supply chain professionals in South Africa does not exceed 1.8 million people, as the total number of people employed in the whole FMCG sector is just over 1.1 million according to the latest Statistics South Africa figures (Statistics South Africa, 2023).

Additionally, this study is aimed primarily at supply chain managers therefore it can be inferred that a sample size much smaller than 300 can give reliable results. Taking into consideration the generally low response rate according to the literature, a target sample size of 200 was pursued in this study. Wei et al. (2020), did a study in China on the effect of top management participation on digital supply chain management and only sampled 190 participants. Given that this study happened in China, which has a much bigger population than South Africa, it was assumed that the target sample size of 200 was representative and that the research outcomes could be relied upon for decision-making.

4.3.4 Measurement Instrument

A measuring instrument is used to measure specific constructs of interest and allows for data collection to be done in a consistent, systematic and objective manner to answer research questions (Rahi et al., 2019). Figure 1b represents the conceptual model that defined this research study. The independent variable is digital maturity, and the dependent variable is SCR with digital innovation acting as a mediator in the proposed conceptual model framework. The mediator, which is digital innovation in this case explains why digital maturity leads to SCR. The control variables kept constant in this study include minimum management experience, type of industry and the emerging market of interest, South Africa in this case.

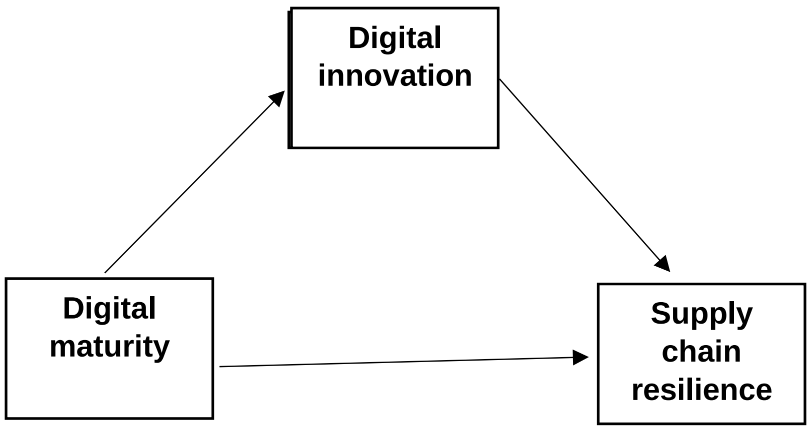

Figure 1b: Conceptual model for the study

The industry was restricted to the FMCG industry, and only experienced supply chain professionals with over five years of management experience who work for organisations in South Africa were considered. A survey questionnaire was used as a measuring instrument in this research study to understand if digital maturity has a positive influence on digital innovation which then leads to SCR. A survey questionnaire is an appropriate tool to use when a researcher is looking for a large amount of data to understand a phenomenon or framework (Rahi et al., 2019). This aligns with the intention of this study as described by the conceptual model in Figure 1b. The FMCG industry in South Africa contributes 20% of the country's GDP, which indicates that many supply chain companies exist in the FMCG industry in South Africa, and a tool that can efficiently gather large amounts of data is needed.

A researcher must take time to design a survey instrument such that it is clear, valid, reliable and relevant to the objective of the research and the target population (Rahi et al., 2019). Consequently, it is common practice to use or modify a survey instrument that has been used before in the literature with similar research objectives and populations of study (Rahi et al., 2019). The survey instrument to be used in this study is adapted from the work of Zouari et al. (2021) and Del Giudice et al. (2021) to gain an understanding of the relationship between digital maturity and digital innovation, and how this influences SCR of manufacturing companies. The instrument has been amended to focus on large FMCG firms in South Africa, with the indirect impact of digital innovation on digital maturity and SCR being evaluated. The draft questionnaire can be found in Appendix 1.

4.4 Pilot Study

A pilot study was conducted over 8 days with 10 respondents. The purpose of the pilot study was to test for technical issues and clarity of the survey questions. The time taken to complete the survey was also evaluated. The pilot study participants were also asked for feedback on their comprehension of the questions and ease of use of the questionnaire.

Feedback was received with several issues and opportunities highlighted by the pilot study respondents. The survey questionnaire was too long as it had 92 questions, the time taken to complete it was 20 minutes on average, and two questions had spelling errors on the Likert scale options. The questionnaire was modified by combining questions, reducing the total number of questions to 66, and the average time to complete was reduced to 13 minutes on average. The spelling errors were rectified on the two questions on the Likert-scale options.

Other checks were conducted to ensure the quality of the data and the success of the data collection process. It was confirmed that the questionnaire can be accessed on a mobile device as well as a desktop, and both versions were readable and user-friendly. Additionally, the data was confirmed to be stored in the specified storage location as the pilot study respondents completed the survey.

One respondent was able to complete the survey twice, and there was no mechanism for filtering this data out from the collected data. Two extra questions were added to allow for the exclusion of duplicate data from a single respondent. One asks for the respondent's age, and another asks for the actual number of years of experience. The final questionnaire with 68 questions was then distributed, and data collection began.

These extra questions together with other identifiers like date and time of completion, gender, seniority, functional area, company age and size were then used during data cleaning to check for data that would have come from the same respondent.

4.5 Data Collection

The data collection process that was followed in this research study is similar to that outlined by the work of Kurzhals & Kurzhals (2021). The data-gathering steps are preceded by the research question formulation, identification of data variables, selection of sampling strategy and the selection of the instrument which has been designed or amended to be able to answer the research questions. Table 1 summarises the data-gathering process that was followed in this research study as well as the rationale and desired outcome of each step.

Table 1: Data gathering process

Data gathering process	**Rationale**	**Outcome**
1. Pilot testing involving a few of the supply chain professionals	To check if it is clear and understandable.	Feedback from the participants on errors, and long unclear questions was used to amend and improve the instrument as outlined in section 4.4.
2. Finalisation of the survey questionnaire	To ensure that the improvement opportunities identified in Step 1 are addressed.	A tested and improved instrument that will achieve research objectives and answer the research questions. It took an average of 13 minutes and 44 seconds to complete.
3. Confirm an appropriate sampling strategy.	To ensure that the proposed sampling method is appropriate for the instrument being used.	A non-probability sampling strategy using purposive sampling was deemed fit for this research study based on the need to focus on supply chain professionals with a minimum of five years of working experience in supply chain management.
4. Distribution of the survey online to maximise reach.	To maximise reach, the online survey was shared via LinkedIn to reach out to participants who fit the criteria.	A total of 205 valid responses were achieved. Meeting the minimum sample size required to perform the Structural Equation Modelling analysis (Thakkar, 2020).
5. Monitor the data collection process, addressing any concerns participants may experience.	To ensure that issues with the survey that may have been missed during the pilot phase are addressed as early as possible so they do not affect the validity of the results.	Participants could not submit the survey after 200 responses because of a restriction placed by the free version of Microsoft Forms. The version was upgraded to allow for more responses.

Adapted from the work of Kurzhals & Kurzhals (2021)

4.6 Data Analysis

The collected data through Microsoft Forms was stored on a personal drive in Microsoft Excel format. The data cleaning, screening and coding were done in Microsoft Excel before the data was imported to IBM Statistical Package for Social Sciences (SPSS) version 28. After conducting descriptive statistics, the data was then analysed to understand the relationship between variables, an appropriate statistical method needs to be selected based on the intention of the study (Pentang & Pentang, 2021). In this study, Structural Equation Modelling (SEM) was used as it is the method of choice when it comes to evaluating complex relationships among variables and also allows for mediation analysis (Thakkar, 2020).

The SEM results indicated a relationship among the variables, which is supported by data that gives a well-fitting model (Thakkar, 2020). This allowed conclusions to be drawn about the relationship between the variables of interest and the statistical significance of the results.

4.6.1 Data screening and cleaning

The first step of data analysis involved data cleaning and preparation whereby errors, missing values, outliers, and irrelevant data are removed from the dataset to ensure it does not skew the study results (Pentang & Pentang, 2021).

4.6.2 Descriptive statistics

The next step involved doing descriptive statistics on the dataset to understand the data in terms of measures of central tendency, while we may not make conclusions based on descriptive statistics it gives a perspective on the main characteristics of the data collected (Pentang & Pentang, 2021). This helped to gain insight into the profile of the respondents in terms of gender, seniority, functional area, company age and size. Further descriptive statistics analysis was done on the dependent, independent, and mediation variables to understand the spread and central tendency of the variables. The central tendency was evaluated using the mean (M) and median (Md), and the spread using the standard deviation (SD). Normal distribution of the data was tested using skewness and kurtosis, with values of -2 to +2 considered acceptable for assuming normal distribution (George et al., 2010).

4.6.3 Inferential statistics and hypothesis testing

A multivariate validity and reliability analysis was conducted, and the results are summarised under quality control. The relationship between the variables and the hypothesis was tested using covariance-based structural equation modelling (CB-SEM). CB-SEM was selected as the method for hypothesis testing as it allows for testing multiple hypotheses and complex relationships involved (Hair et al., 2019).

This study involved three constructs, where both direct and indirect effects were being tested. H1 and H2 tested the direct effects, and H3 tested the indirect effects(mediation). CB-SEM also allows for the handling of latent variables, as in this case the constructs of digital maturity, digital innovation and supply chain resilience are abstract concepts measured using multiple indicators through a questionnaire (Hair et. al., 2019). CB-SEM has predictive capabilities, and it is the method of choice for studies where the objective is theory testing and confirmation (Hair et al., 2019).

This study aimed to understand the impact of digital maturity and digital innovation on supply chain resilience in a South African FMCG industry context, making it a predictive and theory-confirmation research study. This further supports the use of CB-SEM as the method of choice for hypothesis testing. CB-SEM is sensitive to sample size and non-normal data (Hair et al., 2019).

4.6.4 Correlation matrix

The Pearson product-moment correlation was used to determine the strength of the relationships between digital maturity, digital innovation and supply chain resilience. The relationship was deemed statistically significant at p-values < 0.05 for positive and negative correlations. The guidelines of Cohen (1988) were used to infer the strength of the relationships. As per the guidelines, for r values between 0.1 and 0.29, the correlation is deemed to be weak, whereas r values of 0.3 to 0.49 are indicative of medium strength with r values greater than 0.5 indicating a strong relationship between the constructs.

4.6.5 Rationale for factor analysis

The collected data was analysed and interpreted using SPSS version 29. The inferential statistical technique, CB-SEM, was used to analyse the data in SPSS. Before conducting structural equation modelling, factor analysis was done in SPSS.

Factor analysis was used to simplify and reduce the number of items from the survey into broader dimensions (Shrestha, 2021). Factor analysis identifies and allows for verification of how well the survey items measure the latent constructs (Shrestha, 2021; Purwanto & Sudargini, 2021). Common factors can then be identified, which helps understand the relationship between variables, simplifies complex models and allows for easier data interpretation when SEM is conducted. Furthermore, it serves as a form of measurement scale validation for the constructs and reduces multicollinearity of the variables ensuring that model fit, estimation and parameter estimation do not affect the results of the SEM analysis. A confirmatory factor analysis (CFA) was used in this study as a theoretical model had already been proposed, and the analysis aimed to test whether the data fits the hypothesised model structure and to conduct construct validity (Sujati & Akhyar, 2020). CB-SEM was then conducted, and conclusions were drawn and presented at a population level (Purwanto & Sudargini, 2021).

4.7 Quality Controls

Quality control is critical to ensure the quality of the data collected, and this was achieved through quality control measures at the various stages of the research study (Moore et al., 2021). Finding errors as early as possible and rectifying them is crucial to ensuring the quality of the data collected (Moore et al., 2021). The first step was to ensure that the questionnaire design was done correctly, this was key as the instrument must be able to measure the constructs of interest in the study (Moore et al., 2021). In this study, a questionnaire from a previous study was used to mitigate the risk of not doing this correctly due to resource constraints.

The second step taken to ensure the quality of the data collected was to do a pilot testing of the questionnaire to identify and correct errors or anything ambiguous in the survey questionnaire (Moore et al., 2021). Once the instrument had been confirmed to be in order and it was ready to be sent out, care was taken to ensure there were clear and unambiguous instructions for the research study participants as per pilot study findings (Moore et al., 2021). This was to ensure that there were minimal to no missing values or outliers as a result of misunderstanding. Response bias in research occurs when the participants give incorrect data, and this can be due to the order of the questions in the survey (Elston, 2021). The questions were not randomised to mitigate this, and the same order was used for every participant.

Furthermore, to ensure that the quality of the data being collected was not compromised, continuous monitoring of the data entry was done with data validation checks done during the data collection phase. According to Moises (2020), consistent and continuous data monitoring during the data collection phase of the research is more important in online surveys to ensure data quality issues are addressed timeously.

4.7.1 Reliability

Reliability in research means you must get the same results when using the same technique to do the same study (Babbie, 1995). Reliability ensures the integrity of the research by evaluating the consistency of the methodology. In quantitative research, there are two requirements to satisfy reliability: the study's results must be replicable, and the measuring instrument must be consistent over time and amongst different respondents (Dolnicar et al., 2022). The reliability of a study can be affected by observer bias, observer error, participant error, and subject error, which affect the replicability and stability of the measurement instrument (Karunarathna et al., 2024).

In this research study, to help achieve reliability the following measures were taken; Peer-reviewed and highly rated journal sources were used for the literature review. The measuring instruments used were from peer-reviewed and highly-rated journal sources. The statistical technique, Structural Equation Modelling, is typically used for similar studies. The statistical analysis was done in SPSS (Statistical Package for Social Sciences), which is a reliable software typically used for various studies. The data collected was stored electronically and handed to GIBS for safe storage for up to 10 years.

Cronbach's alpha is a statistical measure of internal consistency used to assess the reliability of an instrument through the determination of the average correlation of its variables concerning a single underlying construct (Hair et al., 2019). Hair et al. (2019) state that a Cronbach's alpha of above 0.6 is considered good enough for an instrument. The instruments used to measure all three constructs in this study were found to be good enough, indicating that the instrument used in this study is reliable. A detailed outline of the reliability coefficients is presented in chapter five.

4.7.2 Validity

Data validation is a way of ensuring that the data collection process results in the intended data being collected successfully (Welman & Kruger, 2001). Validity is the extent to which what is being empirically measured can be representative of the real-world meaning of the matter being investigated (Babbie, 1995).

4.7.2.1 Face validity

As a first step in the validity process, face validity was conducted. Face validity involves assessing on the surface if an instrument measures what it aims to measure (Nevo, 1985). It is basic and subjective relying on judgement from experts or survey respondents (Nevo, 1985). In this study this was conducted during the pilot study, where the participants were asked for feedback on the items in the study in terms of relevance and if they are understandable. Face validity is insufficient to confirm validity, and other forms are often needed (Mohajan, 2017). In this study, the Pearson correlation was used to assess survey questions validity. CFA was used to test for construct validity by determining if the items load on the intended factors.

4.7.2.2 Construct validity: CFA

The factor analysis was run using the principal component analysis (PCA) method. The results of grouping the questions to the component on which it loads the highest is summarised in Chapter 5 together with the other CFA output. It was found that all the questions had at least one correlation above 0.3, this implied they were good enough for the factor analysis to continue (Ratner, 2009).

Digital Maturity

The variables had a Kaiser-Meyer-Olkin measure of sampling adequacy of 0.91 which is greater than 0.9 implying that the sampling adequacy of digital maturity by the questions was marvellous and factor analysis is appropriate (Kaiser, 1974). Bartlett’s test of sphericity had a p-value of less than 0.001, indicating that PCA is a suitable method of extraction as the p-value is ≤ 0.05 (Kaiser, 1974). The components were then extracted using the specified Eigenvalue 1 rule (Karlis et al., 2003), and three components were thus extracted representing 66.70% of the total variance.

Digital Innovation

The variables had a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of 0.71 indicating that the sampling adequacy of digital innovation by the questions was good enough as it is much greater than the minimum KMO value of 0.5 required for the factor analysis to be deemed appropriate (Kaiser, 1974). Bartlett's test of sphericity had a p-value of less than 0.001, indicating that PCA is a suitable method of extraction as the p-value is ≤ 0.05 (Kaiser, 1974). The components were then extracted using the specified Eigenvalue 1 rule (Karlis et al., 2003), and one component was thus extracted representing 70.59% of the total variance.

Supply Chain Resilience

The variables had a Kaiser-Meyer-Olkin measure of sampling adequacy of 0.92 which is greater than 0.9 indicating that the sampling adequacy of digital maturity by the questions was marvellous and factor analysis is appropriate (Kaiser, 1974). Bartlett's test of sphericity had a p-value of less than 0.001, indicating that PCA is a suitable method of extraction as the p-value is ≤ 0.05 (Kaiser, 1974). The components were then extracted using the specified Eigenvalue 1 rule (Karlis et al., 2003), and ten components were thus extracted representing 65.42% of the total variance.

Confirmatory Factor Analysis

A confirmatory factor analysis was done to verify construct validity by testing for convergent and discriminant validity. Convergence validity was initially checked by evaluating the factor loadings between each observed variable and the latent variable to test for the strength of the relationship (Shrestha, 2021). All the questions had a factor loading of > 0.5, implying they all adequately represent the construct, making a case for convergent validity (Shrestha, 2021). Most questions had a higher loading of greater than 0.7, which indicates a strong relationship with the latent construct further supporting convergent validity (Shrestha, 2021). A detailed outline of factor loadings for the survey questions is given in Chapter 5.

The Average Variance Extracted (AVE) was calculated and found to be greater than 0.5 for all the latent variables, implying that the study's digital maturity, digital innovation and supply chain resilience indicate good convergent validity (Shrestha, 2021). Composite reliability(Add)

The overall fit of the model was tested in SPSS Analysis of Moment Structures (AMOS); the Chi-square (χ^2), the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Standardised Root Mean Square Residual (SRMR) indicators were used to assess if the proposed factor structure is valid (Widaman & Helm, 2023). All four indicators met the conditions for a good fit, and this provided further evidence of construct validity (Widaman & Helm, 2023). Discriminant validity was also checked to verify that the constructs in the study were adequately different from one another indicating that the latent variables represent distinct concepts (Rönkkö & Cho, 2022). The discriminant validity was checked using the cross-loading and Heterotrait-Monotrait Ratio (HTMT) methods. Discriminant validity was found not to be an issue using both methodologies, supporting the overall validity of the survey instrument used in this study (Rönkkö & Cho, 2022).

4.7.3 Ethical considerations

Ethical clearance was acquired from the University of Pretoria's Gordon Institute of Business School (GIBS) ethics committee before the commencement of data collection. The data collected was stored electronically and handed to GIBS for safe storage on a password-protected cloud facility for a minimum period of 10 years. The participants were informed and assured of the anonymity of their participation; furthermore, they were given the option to withdraw at any point, as their participation was voluntary and was in line with the University of Pretoria's GIBS ethical clearance policy. Participants were also provided with the contact details of a representative of GIBS and the researcher to enable correspondence if required.

4.8 Limitations

This study was biased towards large enterprises in the FMCG industry in South Africa, as 76% of the respondents were from large enterprises. Further research will need to be conducted to confirm the applicability of the results of this study to other emerging markets and industry types with a bigger representation of smaller enterprises. The target sample size for this study was also minimised based on resource constraints, potentially compromising the sample representativeness of the population. However, care was taken to ensure the minimum sample size as defined by previous studies and the literature was met (MacCallum et al., 1999). The study findings are also limited to the views of the supply chain managers. Engaging other human resources in the organisation, such as the supply-chain shop floor, may yield different results. However, they are the right audience to do this study with as they will have a full view of the entire supply chain instead of shop floor workers whose perceptions may be restricted to their functional area.

The unidimensional nature of the digital innovation construct was probably due to the three-item scale used in this study. However, similar studies also used scales with few items for this construct (Del Giudice et al., 2021).

To get a model fit for the CFA and the final SEM, item deletion had to be done, as the low-loading items causing a model misfit were not theoretically relevant to other items to allow for item grouping. Item deletion could have led to the loss of crucial information that the items were measuring. However, it is best practice to delete items with low loading factors if they cannot be combined with other items due to a lack of theoretical justification (Sujati & Akhyar, 2020).

CHAPTER 5 – RESULTS OF THE STUDY

5.1 Introduction

This section of the research report gives the study results, which aim to understand the relationship between digital maturity, digital innovation, and SCR in the context of the South African FMCG industry. The quantitative survey design, data collection and data analysis techniques outlined in Chapter 4 were used to investigate the relationships between the constructs of interest. This results section is organised into data screening and cleaning, descriptive statistics, reliability and validity testing, confirmatory factor analysis and hypothesis testing. Furthermore, this chapter provides an overview of the key themes and correlations that have been discovered from the data analysis.

5.2 Data screening and cleaning

Data screening and cleaning were conducted by evaluating normal distribution, systematic bias, extreme outliers, and missing values. Of the 58 items with 206 data entries for each assessed using the z-scores rule, 38 were extreme outliers. All of these had z-scores outside the allowed threshold of ± 3.29 (Pentang & Pentang, 2021).

For the digital maturity construct, three variables had extreme outliers, DM12 had four, followed by DM13 with two and DM9 with only one extreme outlier value. Digital innovation had only one variable with extreme outliers, DI2 which had two extreme outlier values. Supply chain resilience had nine variables with extreme outliers. SCR19 and SCR27 had four extreme outlier values, followed by SCR12, SCR18 and SCR25 with three extreme outlier values, SCR21, SCR22, SCR26 and SCR31 all had two extreme outlier values, and SCR1, SCR14, SCR23 and SCR34 all had one extreme outlier value. These values were deleted as per the best practice of handling extreme outliers in datasets, and the remaining data had z-scores within the acceptable range of ±3.29 (Pentang & Pentang, 2021).

The data trimming resulted in missing data for some of the variables, missing data can skew a study's statistical results which can lead to incorrect statistical output, findings and recommendations (Bannon, 2015). To avoid this, the missing data should be within acceptable levels of below 5% of the total values of a variable

(Bannon, 2015). For this study, the missing data percentage for all the variables involved was found to be less than 5%, with the highest being 1.9% implying the missing data was within acceptable limits.

The validity of the relationships between the constructs can be negatively affected by the common method bias (CMB) which results in systematic bias exaggerating or understating correlations between constructs (Podsakoff et al., 2024). The CMB was evaluated using Harman's single-factor test, a commonly used approach (Kock, 2020). The test states that if the first factor accounts for greater than 50% of the total variance, a CMB problem is likely to occur (Kock, 2020). It was confirmed that there is no CMB problem in this research study as the variance was found to be 32.36% for digital maturity and 13.95% for supply chain resilience, and digital innovation was found to be unidimensional.

5.3 Descriptive Statistics

5.3.1 Profile of the respondents

Table 2 summarises the profile of the respondents. A total of 206 valid responses were attained from people who work in the South African FMCG industry with a minimum of five years of supply chain management experience. The mean age of the respondents was 37.72 years old with a median of 37 years old. The youngest respondent was 25 years old, and the oldest respondent was 60 years old. The number of years of experience in supply chain management of the respondents ranged from 5 years to 38 years old, with a mean and median of 11 years and 12.2 years respectively. Approximately six people in every ten people were males (57.28%) and about four females (42.23%) in every ten people. The level of representation in terms of seniority had people in middle management as the group with the highest representation at 42.72% with junior and senior management groups being almost equal in terms of representation at 25.73% and 23.79% respectively. The executive managers had the lowest representation at only 7.77%.

Most of the respondents worked in the production functional area at 51.94%, with engineering and customer service departments having the lowest representation at 7.28% and 6.80% respectively. Most respondents worked for organisations that have been operating in the South African market for more than 50 years (34.95%). Other respondents worked for companies that had been in the market for 20 to 50 years

(26.21%), 10 to 20 years (28.64%), 5 to 10 years (8.74%) and less than 5 years (1.46%). More than half of the respondents worked for companies which employed more than 5000 employees (33.98%) or between 1000 to 5000 employees (27.67%). The group with the lowest representation was that of those respondents working for companies with less than 100 employees (4.85%).

Table 2. Profile of the respondents

		Frequency	% Frequency
Do you work in the FMCG supply chain industry in South Africa?	Yes	228	75%
	No	76	25%
Do you have a minimum of 5 years of experience in SCM (Supply Chain Management)	Yes	206	90.35%
	No	22	9.65%
What is your gender?	Woman	87	42.23%
	Man	118	57.28%
	Non-binary	0	0%
	Prefer not to say	1	0.49%
Level of seniority in your organisation?	Junior management	53	25.73%
	Middle management	88	42.72%
	Senior management	49	23.79%
	Executive management	16	7.77%
Which supply chain industry sector best describes your functional area?	Production	107	51.94%
	Quality assurance	23	11.17%
	Planning, Procurement and Logistics	36	17.48%
	Engineering	15	7.28%
	Customer service	14	6.80%
	Other	11	5.34%
How long has your organisation operated in South Africa?	Less than 5 years	3	1.46%
	5 to 10 years	18	8.74%
	10 to 20 years	59	28.64%
	20 to 50 years	54	26.21%
	More than 50 years	72	34.95%
What is your company size (In South Africa)?	Less than 100 employees	10	4.85%
	100 to 499 employees	39	18.93%

	500 to 999 employees	30	14.56%
	1000 to 5000 employees	57	27.67%
	More than 5000 employees	70	33.98%

5.3.2 Descriptive statistics of the main variables

5.3.2.1 Digital maturity

The study's independent variable was digital maturity; it initially had 14 items evaluated using a 5-point Likert scale where 1 indicated strongly disagree, and 5 indicated strongly agree. The 14 items were reduced to 13 after one was deleted and found unreliable. Table 3 summarises the descriptive statistics for the 13 items used to assess digital maturity. The survey results indicated that respondents highly agreed with DM12, stating, “We ensure information security” (M = 4.48, Md = 5.00 and SD= 0.59). It was followed by DM9, which stated, “Data we collect helps manage orders from customers’’ (M = 4.11, Md = 4.00 and SD = 0.76) and then DM11, which stated, “We have tools for data sharing’’ (M = 4.04, Md = 4.00 and SD = 0.73). The item with which the respondents least agreed was DM7, “Data we collect allows "pay-per-use" models to be used in our business” (M = 3.33, Md = 3.00 and SD = 0.98). The range for skewness was -0.99 to -0.25, and for kurtosis, it was -0.64 to 1.38, within the -2 to 2 range for normally distributed data (Hair et al., 2010).

Table 3. Descriptive statistics of digital maturity

Digital maturity Items		Mean (M)	Median (Md)	Standard deviation (SD)	Skewness	Kurtosis
SCM team has skills for digital transformation and a digital mindset.	DM1	3.84	4.00	0.92	-0.77	0.05
We provide digital training for SCM.	DM2	3.55	4.00	1.07	-0.66	-0.21
We have a leader in digital Supply Chain (SC) transformation	DM3	3.75	4.00	1.09	-0.70	-0.42
We have a digital program agenda and processes for managing digital programs.	DM4	3.67	4.00	0.99	-0.68	-0.28

We allocate resources for the digital SC program.	DM5	3.59	4.00	1.05	-0.57	-0.55
We understand advanced digital SC tools.	DM6	3.45	4.00	1.08	-0.56	-0.60
Data we collect allows "pay-per-use" models to be used in our business.	DM7	3.33	3.00	0.98	-0.25	-0.64
Data we collect helps manage returns from customers.	DM8	3.93	4.00	0.86	-0.76	-0.19
Data we collect helps manage orders from customers.	DM9	4.11	4.00	0.76	-0.93	1.17
Data we collect helps manage maintenance.	DM10	3.90	4.00	0.93	-0.99	0.94
We have tools for data sharing	DM11	4.04	4.00	0.73	-0.89	1.38
We ensure information security	DM12	4.48	5.00	0.59	-0.65	-0.53
We support data-driven processes.	DM13	4.16	4.00	0.80	-0.98	0.91

5.3.2.2 Digital innovation

The mediating variable of the study was digital innovation; it had three items that were also evaluated using a 5-point Likert scale where 1 denoted strongly disagree, 2 disagree, 3 neutral, 4 agree, and 5 denoted strongly agree. Table 4 summarises the descriptive statistics for the 3 items to assess digital innovation. The survey results showed that respondents highly agreed with DI2, which stated, “We use digital workplace technology” (M = 4.02, Md = 4.00 and SD = 0.84). It was followed by DI1, which stated, “We use big data, IoT for innovation’’ (M = 3.54, Md = 4.00 and SD = 1.09). The item with which the respondents least agreed was DI3, “We employ digital tech for new ideas” (M = 3.53, Md = 4.00 and SD = 1.02). The range for skewness was -0.86 to -0.33, and for kurtosis, it was -0.83 to 0.48, within the -2 to 2 range for normally distributed data (Hair et al., 2010).

Table 4. Descriptive statistics of digital innovation

Digital innovation Items		Mean (M)	Median (Md)	Standard deviation (SD)	Skewness	Kurtosis
We use big data, and IoT for innovation.	DI1	3.54	4.00	1.09	-0.40	-0.57
We use digital workplace technology.	DI2	4.02	4.00	0.84	-0.86	0.48
We employ digital tech for new ideas.	DI3	3.53	4.00	1.02	-0.33	-0.83

5.3.2.3 Supply chain resilience

The study's dependent variable was supply chain resilience; it had 42 items that were evaluated using a 5-point Likert scale where 1 indicated strongly disagree, and 5 indicated strongly agree. Table 5a summarises the descriptive statistics for the top five SCR items that respondents highly agreed with, and Table 5b summarises the same for the items with which respondents least agreed. The survey results indicated that respondents highly agreed with SCR27: "Products are sold in various regions" (M = 4.51, Md = 5.00 and SD= 0.55). It was followed by SCR34, which stated "Our brands are well-recognized and customers differentiate our products'' (M = 4.44, Md = 5.00 and SD = 0.74), SCR1 which stated "Supplies (e.g. Materials, resources, equipment, and tools) are used in multiple products'' (M = 4.33, Md = 4.00 and SD = 0.71), SCR38 which stated "We run security awareness programs and our information systems are secure'' (M = 4.33, Md = 4.00 and SD = 0.71), and then SCR41 which stated "Our business portfolio is diverse'' (M = 4.33, Md = 4.00 and SD = 0.75).

The item with which the respondents least agreed was SCR33, "We fill leadership voids quickly" (M = 3.36, Md = 4.00 and SD = 1.17). It was followed by SCR6, which stated "We pool inventory centrally and can change shipment routes quickly'' (M = 3.42, Md = 4.00 and SD = 1.02), SCR39, which stated "We collaborate with government on security'' (M = 3.47, Md = 4.00 and SD = 1.00), SCR9 which stated "We have excess capacity for quick boosts'' (M = 3.49, Md = 4.00 and SD = 1.01), and then SCR30 which stated "We invest in supplier facilities and share risks'' (M = 3.56, Md = 4.00 and SD = 0.96).

The range for skewness was -1.55 to -0.25, and for kurtosis, it was -0.76 to 4.31. This indicates that some items failed the kurtosis test as the kurtosis was outside the -2 to 2 range for normally distributed data (Hair et al., 2010).

Table 5a. Descriptive statistics of supply chain resilience for highly agreed items

Supply chain resilience	Items	Mean (M)	Median (Md)	Standard deviation (SD)	Skewness	Kurtosis
Supplies (e.g. Materials, resources, equipment, and tools) are used in multiple products.	SCR1	4.33	4.00	0.71	-0.98	1.10
Products are sold in various regions.	SCR27	4.51	5.00	0.55	-0.52	-0.86
Our brands are well-recognized and customers differentiate our products.	SCR34	4.44	5.00	0.70	-1.20	1.35
We run security awareness programs and our information systems are secure.	SCR38	4.33	4.00	0.71	-1.14	1.89
Our business portfolio is diverse.	SCR41	4.33	4.00	0.75	-1.11	1.23

Table 5b. Descriptive statistics of supply chain resilience for least agreed items

Supply chain resilience	Items	Mean (M)	Median (Md)	Standard deviation (SD)	Skewness	Kurtosis
We pool inventory centrally and can change shipment routes quickly.	SCR6	3.42	4.00	1.02	-0.33	-0.69
We have excess capacity for quick boosts.	SCR9	3.49	4.00	1.01	-0.25	-0.75
We invest in supplier facilities and share risks.	SCR30	3.56	4.00	0.96	-0.44	-0.24
We fill leadership voids quickly.	SCR33	3.36	4.00	1.17	-0.43	-0.76
We collaborate with government on security.	SCR39	3.47	4.00	1.00	-0.39	-0.15

5.4 Reliability and Validity testing

5.4.1 Digital Maturity

An exploratory factor analysis was done on the 13 items of digital maturity. The items had a Kaiser-Meyer-Olkin measure of sampling adequacy of 0.92 and Bartlett's test of sphericity had a p-value of less than 0.001, Chi-Square of 1290.80 and df (degrees of freedom) of 78 indicating that PCA is a suitable method of extraction as the p-value was ≤ 0.05. The components were then extracted using the specified Eigenvalue 1 rule, and three components were thus extracted representing 66.03% of the total variance. This implied that the digital maturity construct is multi-dimensional, as the factor analysis yielded three sub-constructs.

The first subconstruct was named digital competencies, as the seven items that loaded on this factor focused on the organisational competencies in digital supply chain tools. The second subconstruct was named digital value creation, as the four items loaded on this factor focused on how organisations leveraged digital tools to create value for the business. The third subconstruct was named digital security, as the two items loaded on this factor concentrated on how data is shared and secured. Table 6 summarises the loading factors for digital maturity from the PCA extraction method. A confirmatory factor analysis was then done to test for construct validity of digital maturity.

Table 6. Exploratory factor analysis of digital maturity: Loading factors

Items	Digital competencies	Digital value creation	Digital security	% of the total variance	Eigenvalue	Cronbach alpha
DM4	0.81			32.36%	6.27	
DM5	0.79					
DM3	0.76					
DM2	0.75					
DM6	0.74					
DM1	0.67					
DM7	0.59					
DM9		0.84		19.9%	1.20	
DM8		0.81				
DM10		0.58				
DM11		0.56				
DM12			0.83	13.77%	1.12	
DM13			0.75			

5.4.2 Digital Innovation

It was also found that all the questions for the digital innovation construct had at least one correlation above 0.3, this implied they were good enough for the factor analysis to be conducted (Ratner, 2009). The variables had a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of 0.71 indicating that the sampling adequacy of digital innovation by the questions was good enough as it is much greater than the minimum KMO value of 0.5 required for the factor analysis to be deemed appropriate (Kaiser, 1974). Bartlett's test of sphericity had a p-value of less than 0.001, indicating that PCA is a suitable method of extraction as the p-value is ≤ 0.05 (Kaiser, 1974). The components were then extracted using the specified Eigenvalue 1 rule (Karlis et al., 2003), and one component was thus extracted representing 70.59% of the total variance.

Table 7. Exploratory factor analysis of digital innovation

Items	Digital innovation	% of the total variance	Eigenvalue	Cronbach alpha
DI3	0.84	69.14 %	2.07	0.77
DI1	0.83			
DI2	0.82			

5.4.3 Supply Chain Resilience

An exploratory factor analysis on the 42 SCR items revealed a Kaiser-Meyer-Olkin measure of sampling adequacy of 0.91 which is greater than 0.9 indicating that the sampling adequacy of SCR by the questions was marvellous and factor analysis is appropriate (Kaiser, 1974). Bartlett's test of sphericity had a p-value of less than 0.001, indicating that PCA was a suitable method of extraction as the p-value is ≤ 0.05 with a Chi-Square of 4139.72 and df of 861. The components were then extracted using the specified Eigenvalue 1 rule (Karlis et al., 2003), and nine components were thus extracted representing 59.13% of the total variance. This implied that SCR was multi-dimensional characterised by nine subconstructs.

The first subconstruct was named operational agility (SCR-OA), as the 12 items that loaded on this factor focused on the capability of organisations to monitor operations to identify potential disruption and adapt quickly to maintain the efficiency of the supply chain. All the items had good loading factors greater than 0.4 (Maskey & Nguyen, 2018), except for SCR30 which had a loading factor of 0.38. SCR30 was subsequently removed to protect factor validity as the factor loading suggests the item is potentially redundant and may negatively affect the model fit indices for subsequent analyses such as CFA and SEM (Maskey & Nguyen, 2018). The Cronbach's alpha and factor loadings of the remaining items were re-checked after deletion and were found still be reliable and valid. Table 8 summarises the results for the SCR-OA subconstruct from the PCA extraction method. Operational agility (OA) represented 13.95% of the total variance, with an eigenvalue of 14.38 which is greater than 1 (Karlis et al., 2003). The Cronbach's alpha was 0.91, higher than the acceptable value of 0.6 which supported the reliability of the items (Hair et al.,2019).

Table 8. Exploratory factor analysis of SCR: Operational agility

Items	Operational agility	% of the total variance	Eigenvalue	Cronbach alpha
SCR13	0.74	13.95%	14.38	0.91
SCR14	0.68			
SCR15	0.74			
SCR16	0.65			
SCR17	0.70			
SCR20	0.52			
SCR29	0.60			
SCR30	0.38			
SCR12	0.41			
SCR18	0.52			
SCR21	0.47			
SCR10	0.54			

The second subconstruct was named market diversification (SCR-MD), as the six items that loaded on this factor focused on the extent to which the organisation is protected from disruption through diversification of its product portfolio and geographic presence and reach. All the items had good loading factors greater than 0.4 (Maskey & Nguyen, 2018), supporting the items' validity in representing the market diversification factor. Table 9 summarises the results for the SCR-MD subconstruct from the PCA extraction method. Market diversification (MD) represented 8.34% of the total variance, with an eigenvalue of 2.66 which is greater than 1 (Karlis et al., 2003). The Cronbach’s alpha was 0.79, higher than the acceptable value of 0.6 which supported the reliability of the items (Hair et al.,2019).

Table 9. Exploratory factor analysis of SCR: Market diversification

Items	Market diversification	% of the total variance	Eigenvalue	Cronbach alpha
SCR34	0.75	8.34%	2.66	0.79
SCR35	0.69			
SCR36	0.47			
SCR27	0.64			
SCR41	0.48			
SCR25	0.56			

The third subconstruct was named resource agility (SCR-RA), as the five items that loaded on this factor focused on the ability of an organisation to swiftly acquire, reallocate, reconfigure and adapt resources to respond to a changing business environment that threatens its ability to meet market and operational requirements. All the items had good loading factors greater than 0.4 (Maskey & Nguyen, 2018), supporting the items' validity in representing the resource agility factor. Table 10 summarises the results for the SCR-RA subconstruct from the PCA extraction method. Resource agility (RA) represented 8.13% of the total variance, with an eigenvalue of 1.80 which is greater than 1 (Karlis et al., 2003). The Cronbach's alpha was 0.83, higher than the acceptable value of 0.7 which supported the reliability of the items (Hair et al.,2019).

Table 10. Exploratory factor analysis of SCR: Resource agility

Items	Resource agility	% of the total variance	Eigenvalue	Cronbach alpha
SCR4	0.47	8.13%	1.80	0.83
SCR6	0.49			
SCR7	0.74			
SCR8	0.72			
SCR9	0.68			

The fourth subconstruct was named responsive demand management (SCR-RDM), as the four items loaded on this factor are focused on the ability of organisations to adjust demand in real-time in response to supply chain disruptions and market conditions that are driving demand fluctuations. All the items had good loading factors greater than 0.4 (Maskey & Nguyen, 2018), supporting the validity of the items in representing the factor of responsive demand management. Table 11 summarises the results for the SCR-RDM subconstruct from the PCA extraction method. Responsive demand management (RDM) represented 7.16% of the total variance, with an eigenvalue of 1.50 which is greater than 1 (Karlis et al., 2003). The Cronbach's alpha was 0.78, higher than the acceptable value of 0.7 which supported the reliability of the items (Hair et al.,2019).

Table 11. Exploratory factor analysis of SCR: Responsive demand management

Items	Responsive demand management	% of the total variance	Eigenvalue	Cronbach alpha
SCR19	0.50	7.16%	1.50	0.78
SCR22	0.70			
SCR23	0.70			
SCR26	0.49			

The fifth subconstruct was named risk mitigation (SCR-RM), as the four items loaded on this factor focused on an organisation's ability to identify, assess and implement measures to manage potential security risks that could disrupt supply chain operations. All the items had good loading factors greater than 0.4 (Maskey & Nguyen, 2018), supporting the validity of the items in representing the factor of risk mitigation. Table 12 summarises the results for the SCR-RM subconstruct from the PCA extraction method. Risk mitigation (RM) represented 6.26% of the total variance, with an eigenvalue of 1.39 which is greater than 1 (Karlis et al., 2003). The Cronbach's alpha was 0.70, meeting the acceptable value of 0.6, which supports the reliability of the items representing the factor (Hair et al.,2019).

Table 12. Exploratory factor analysis of SCR: Risk mitigation

Items	Risk mitigation	% of the total variance	Eigenvalue	Cronbach alpha
SCR37	0.72	6.26%	1.39	0.70
SCR38	0.78			
SCR39	0.49			
SCR42	0.58			

The sixth subconstruct was named resource flexibility (SCR-RF), as the five items that loaded on this factor focused on the ability of an organisation to adapt its existing resources to respond to a changing business environment that threatens its ability to meet market and operational requirements. All the items had good loading factors greater than 0.4 (Maskey & Nguyen, 2018), except for SCR31 which had a loading factor of 0.34. SCR31 was subsequently removed to protect factor validity as the factor loading suggests the item is potentially redundant and may negatively affect the model fit indices for subsequent analyses such as CFA and SEM (Maskey & Nguyen, 2018). The Cronbach's alpha and factor loadings of the remaining items were re-checked after deletion and were found still be reliable and valid. Table 13 summarises the results for the SCR-RF subconstruct from the PCA extraction method. Resource flexibility (RF) represented 5.92% of the total variance, with an eigenvalue of 1.26 which is greater than 1 (Karlis et al., 2003). The Cronbach's alpha was 0.77, which was higher than the acceptable value of 0.7 which supported the reliability of the items in representing the factor (Hair et al., 2019).

Table 13. Exploratory factor analysis of SCR: Resource flexibility

Items	Resource flexibility	% of the total variance	Eigenvalue	Cronbach alpha
SCR11	0.47	5.92%	1.26	0.77
SCR24	0.58			
SCR31	0.34			
SCR32	0.66			
SCR33	0.63			

The seventh subconstruct was named supply chain flexibility (SCR-SCF), as the three items that loaded on this factor focused on the ability of an organisation's entire supply chain including its internal and external partners to be adaptive and responsive to market conditions and disruptions. All the items had good loading factors greater than 0.4 (Maskey & Nguyen, 2018), supporting the validity of the items in representing the factor of supply chain flexibility. Table 14 summarises the results for the SCR-RM subconstruct from the PCA extraction method. Supply chain flexibility (SCF) represented 5.57% of the total variance, with an eigenvalue of 1.20 which is greater than 1 (Karlis et al., 2003). The Cronbach's alpha was 0.75, meeting the acceptable value of 0.70, which supports the reliability of the items that represent the factor (Hair et al., 2019).

Table 14. Exploratory factor analysis of SCR: Supply chain flexibility

Items	Supply chain flexibility	% of the total variance	Eigenvalue	Cronbach alpha
SCR1	0.70	5.57%	1.20	0.75
SCR2	0.77			
SCR3	0.56			

The eighth subconstruct was named supply chain coordination (SCR-SCC), as the two items that loaded on this factor focused on the ability of an organisation to effectively collaborate throughout the supply chain to respond to customer requirements through optimised inventory management. All the items had good loading factors greater than 0.4 (Maskey & Nguyen, 2018), supporting the validity of the items in representing the factor of responsive demand management. Table 15 summarises the results for the SCR-RDM subconstruct from the PCA extraction method.

Supply chain coordination (SCC) represented 6.26% of the total variance, with an eigenvalue of 1.39 which is greater than 1 (Karlis et al., 2003). The Cronbach’s alpha was 0.46, lower than the acceptable value of 0.7, implying that the items were unreliable in representing the factor (Hair et al.,2019). Pearson’s correlation was run for the two-item subconstruct, and it was found to be less than 0.3 indicating a positive but weak relationship between the two items (Ratner, 2009).

Deleting items is one way to deal with this, but combining them with another subconstruct is preferred as it prevents the loss of important concepts in describing a construct (Emmanuel et al., 2021). This consideration is especially important when the items have good loading factors, as was the case with these items. Combining the items with other subconstructs is only possible if a good correlation and theoretical relevance exist between the other constructs and the items (Sawaki et al., 2009). Because the correlation matrix indicated that SCR5 had no moderate or strong relationship with any of the items as the coefficients with the other items were all below 0.3. While SCR28 had coefficients higher than 0.3 with some items, indicating medium and strong relationships, it did not correlate well with any specific construct. Additionally, it lacked theoretical relevance to other subconstructs. Consequently, both items were deleted as well as the factor from further analysis to ensure that the CFA and SEM do not encounter model fit issues (Sujati & Akhyar, 2020). Furthermore, the removal of the items would not severely affect the construct SCR as it has many other items (DeSimone et al., 2015).

Table 15. Exploratory factor analysis of SCR: Supply chain coordination

Items	Supply chain coordination	% of the total variance	Eigenvalue	Pearson's correlation and Cronbach's alpha
SCR5	0.77	2.44%	1.15	0.299 and 0.46
SCR28	0.53			

The ninth subconstruct was named financial strength (SCR-FS), as the one item that loaded on this factor focused on the margins the organisation makes from its sales and the state of its financial reserves. The item had a good loading factor of greater than 0.4 (Maskey et al., 2018), supporting the validity of the item in representing the factor of financial strength. Table 16 summarises the results for the SCR-FS subconstruct from the PCA extraction method. Financial strength (FS) represented 6.26% of the total variance, with an eigenvalue of 1.02 which is greater than 1 (Karlis et al., 2003). The Cronbach's alpha cannot be calculated for this subconstruct as it is a single-item subconstruct. Single-item subconstructs pose a challenge to check for reliability and sometimes can be candidates for deletion (Fakunmoju, 2020). Due to the relatively high factor loading, the item and subconstructs were not deleted at this data analysis stage (Shrestha, 2021). Furthermore, it correlates well with more than one other item based on the correlation matrix, where multiple coefficients of more than 0.3 with other items (Hair et al.,2019).

Table 16. Exploratory factor analysis of SCR: Financial strength

Items	Financial strength	% of the total variance	Eigenvalue	Cronbach alpha
SCR40	0.59	1.36%	1.02	Not applicable

5.4.4 Discriminant validity and correlation matrix

Discriminant validity is a form of construct validity test that checks if constructs that have no relationship, are indeed different (Rönkkö & Cho, 2022). The Heterotrait-monotrait (HTMT) ratio is a measure of the extent to which two latent variables are similar and was used to evaluate discriminant validity (Yusoff et al., 2020). The HTMT values were all below the threshold of 0.85, as indicated by the HTMT matrices in Tables 17 and 18; this implied that discriminant validity could be confirmed (Kline, 2011).

Table 17. HTMT matrix for discriminant validity evaluation for digital maturity (Initial)

	DMDC	DMDV	DMDS
DMDC	0.72	0.58	0.50
DMDV	0.58	0.74	0.52
DMDS	0.50	0.52	0.74

Table 18. HTMT matrix for discriminant validity evaluation for supply chain resilience (Initial)

	SCR-OA	SCR-MD	SCR-RA	SCR-RM	SCR-RF	SCR-SCF	SCR-FS	SCR-RDM
SCR-OA	1							
SCR-MD	0.53							
SCR-RA	0.65	0.41						
SCR-RM	0.58	0.49	0.52					
SCR-RF	0.73	0.44	0.61	0.69				
SCR-SCF	0.45	0.34	0.40	0.46	0.50			
SCR-FS	0.41	0.36	0.45	0.48	0.56	0.39		
SCR-RDM	0.56	0.42	0.49	0.53	0.60	0.45	0.49	1

Furthermore, discriminant validity was also checked using cross-loadings. The loading factor on the construct of interest must be higher than the loading values on the other constructs to ensure discriminant validity is met (Rönkkö & Cho, 2022). High cross-loadings have a negative effect on the model fit for CFA and SEM, making it difficult to interpret the results and draw conclusions (Li et al., 2020). Cross loadings were checked between the constructs and items, and issues were found as displayed in Table 19 and Table 20.

Table 19. Cross-loading analysis for digital maturity

	Components		
	DMDC	DMDV	DMDS
DM1	0.658	0.249	0.299
DM2	0.742	0.120	0.306
DM3	0.777	0.255	0.138
DM4	0.819	0.200	0.118
DM5	0.792	0.254	0.228
DM6	0.733	0.305	0.261
DM7	0.544	0.521	-0.167
DM8	0.230	0.814	0.086
DM9	0.112	0.836	0.222
DM10	0.331	0.596	0.133
DM11	0.303	0.540	0.414
DM12	0.151	0.113	0.843
DM13	0.361	0.200	0.735
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]			

Table 20. Cross-loading analysis for supply chain resilience

	Components								
	1	2	3	4	5	6	7	8	9
SCR1	0.083	0.063	0.040	0.186	0.093	0.119	0.739	0.097	0.079
SCR2	0.064	0.063	0.142	0.143	0.070	0.117	0.789	0.077	-0.053
SCR3	0.148	0.236	0.150	0.217	0.256	0.013	0.551	0.099	0.189
SCR4	0.245	0.428	0.163	0.247	0.328	0.064	0.193	0.156	0.114
SCR5	-0.034	0.103	0.045	-0.213	0.026	0.070	0.371	0.694	0.032
SCR6	0.254	0.439	0.077	0.097	0.383	0.033	0.188	0.124	0.224
SCR7	0.144	0.390	0.178	0.118	0.680	0.108	0.167	-0.017	0.120
SCR8	0.222	0.125	0.126	0.096	0.754	0.073	0.105	-0.029	0.134
SCR9	0.128	0.411	0.124	0.129	0.571	0.188	0.206	0.180	-0.072
SCR10	0.407	0.632	0.116	0.012	0.124	0.137	0.240	-0.118	-0.021
SCR11	0.347	0.634	0.156	-0.043	0.232	0.042	0.082	-0.067	0.045
SCR12	0.343	0.363	0.358	0.034	0.058	0.269	0.242	-0.114	-0.106
SCR13	0.728	0.270	0.229	0.137	0.158	0.107	-0.080	0.032	0.001
SCR14	0.737	-0.010	0.148	0.082	0.039	0.156	0.139	-0.088	0.170
SCR15	0.693	0.255	0.222	0.045	0.249	0.119	0.090	0.230	0.003

SCR16	0.602	0.337	0.055	0.057	0.162	0.138	0.230	0.045	0.176
SCR17	0.636	0.299	0.228	0.101	0.200	0.031	0.045	0.073	0.087
SCR18	0.444	0.148	0.590	0.258	0.014	0.024	0.213	0.124	-0.177
SCR19	0.291	0.122	0.462	0.322	0.012	0.200	0.135	0.164	0.257
SCR20	0.461	0.194	0.445	0.151	0.054	0.183	0.170	0.165	0.084
SCR21	0.413	0.147	0.536	0.186	0.228	0.089	0.133	0.242	-0.025
SCR22	0.133	0.156	0.679	0.060	0.358	0.110	0.117	-0.029	0.295
SCR23	0.190	0.232	0.749	-0.002	0.193	0.133	0.052	0.056	0.124
SCR24	0.019	0.623	0.266	-0.061	0.138	0.147	0.077	0.275	0.181
SCR25	0.203	0.018	-0.041	0.481	0.109	0.263	0.237	0.185	0.341
SCR26	0.200	0.142	0.208	0.023	0.125	0.149	0.071	0.065	0.744
SCR27	0.033	0.064	0.144	0.574	-0.194	0.173	0.301	-0.042	0.264
SCR28	0.264	0.115	0.167	0.302	0.078	0.198	0.032	0.595	0.096
SCR29	0.519	0.306	0.239	0.209	0.242	0.071	-0.072	0.336	0.245
SCR30	0.366	0.330	0.268	0.312	0.191	0.030	-0.084	0.273	-0.053
SCR31	0.184	0.350	0.495	0.255	-0.055	0.246	0.125	-0.019	0.012
SCR32	0.178	0.471	0.339	0.244	0.198	-0.076	-0.063	0.195	0.215
SCR33	0.274	0.495	0.386	0.073	0.121	-0.016	0.022	0.069	0.204
SCR34	0.062	-0.006	0.070	0.768	0.119	0.143	0.255	0.031	-0.044
SCR35	0.209	0.070	0.274	0.706	0.204	0.079	0.059	-0.046	-0.014
SCR36	0.326	0.178	0.403	0.400	0.095	0.286	-0.074	0.219	0.016
SCR37	0.278	0.187	0.131	0.157	0.026	0.688	0.035	0.119	0.097
SCR38	0.103	-0.081	0.069	0.231	0.172	0.761	0.225	0.080	0.069
SCR39	0.272	-0.040	0.179	-0.056	0.489	0.391	-0.085	0.225	-0.185
SCR40	0.196	0.513	0.103	0.253	0.028	0.271	-0.031	0.187	-0.189
SCR41	-0.045	0.217	-0.016	0.483	0.077	0.463	0.050	-0.073	-0.124
SCR42	0.070	0.188	0.243	0.110	0.116	0.606	0.111	0.061	0.197
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.									

The criteria used to identify and delete items with high cross-loadings were as follows; any item which had a loading of more than 0.3 on more than one factor, and the primary factor was less than 0.5 or the differences between the loadings was less than 0.1 was regarded as having a high cross-loading (Hair et al., 2010). Digital maturity had two items with high cross-loadings that were deleted to ensure discriminant validity was not violated. The items were DM7 and DM11. SCR had 16 items with high cross-loadings that were deleted, and the items were SCR4, SCR6, SCR9, SCR12, SCR18 - SCR21, SCR25, SCR29 - SCR33, SCR36, SCR39 and SCR41. The initial digital maturity model tested in CFA then had 11 items and the three subconstructs extracted from the EFA, whereas the initial supply chain resilience CFA model had 24 items and the nine subconstructs extracted from the EFA.

The discriminant validity was also checked using the Fornell-Larcker criterion after conducting the CFA. The Fornell-Larcker criterion states that discriminant validity is met if the square root of the average variance extracted is greater than the correlation between the construct of interest and any of the other constructs (Mohd Dzin & Lay, 2021; Rönkkö & Cho, 2022). The square root of the average variance per subconstruct is summarised in Table 21, and the correlations between the constructs are in Table 22. Except for DI and SCR-OA, discriminant validity was found not to be an issue, as the square root of the average variance extracted was greater than the correlation between the construct of interest and any of the other constructs. While the Forell-Lacker criterion failed and did not support discriminant validity between DI and SCR-OA, a decision was made to proceed with the CFA as the HTMT method supported discriminant validity. The HTMT method is deemed more reliable, sensitive and robust than the Fornell-Larcker criterion (Dirgiatmo, 2023).

Table 21. AVE and Square root of AVE of each construct

Constructs	AVE	Square root of AVE
DMDC	0.65	0.80
DMDV	0.66	0.81
DI	0.54	0.73
SCR- OA	0.58	0.76
SCR- MD	0.56	0.75
SCR- RDM	0.67	0.82
SCR- SCF	0.59	0.77
SCR- RA	0.65	0.80

Table 22. Pearson product-moment correlations between the constructs of interest

	DMDC	DMDV	DI	SCR-OA	SCR-MD	SCR-RDM	SCR-SCF	SCR-RA
DMDC								
DMDV	0.59							
DI	0.79	0.63						
SCR- OA	0.65	0.55	0.81					
SCR- MD	0.37	0.49	0.47	0.44				
SCR-RDM	0.47	0.39	0.47	0.64	0.43			
SCR-SCF	0.39	0.45	0.45	0.31	0.50	0.35		
SCR- RA	0.56	0.40	0.52	0.62	0.43	0.62	0.35	

The results of the correlation matrix in Table 22 show that digital competency (DMDC) had a statistically significant, positive and strong relationship with digital value creation (DMDV), digital innovation (DI), operational agility (SCR-OA), and resource agility (SCR-RA) because the correlation coefficients (r values) were greater than 0.5 at the defined confidence interval (95% in this study, p-value of less than 0.05) as per guidelines of Cohen (1988). DMDV also had a statistically significant, positive and strong relationship with DI and SCR-OA. Similarly, SCR-OA had a statistically significant, positive and strong relationship with responsive demand management (SCR-RDM). Market diversification (SCR-MD) with supply chain flexibility (SCR-SCF), DI with SCR-RA, SCR-OA with SCR-RA and SCR-RDM with SCR-RA. These subconstruct correlations adhered to the threshold Cohen (1988) outlined for significant, strong, positive relationships. The remaining relationships between the subconstructs had r values of between 0.35 and 0.49 with p-values of less than 0.05, indicating a significant, moderate relationship between the subconstructs as per the guidelines of Cohen (1988).

5.5 Confirmatory Factor Analysis

A CFA was then conducted to validate the measurement models and to also assess construct validity (Shrestha, 2021). That is, to measure that the items measure the latent variables and evaluate if they capture their intended meanings (Shrestha, 2021). The analysis was done in SPSS AMOS version 29, and a confidence interval of 95% (p-value < 0.05) was deemed sufficient for the statistical significance of the results.

5.5.1 CFA: Digital maturity

The initial CFA model was not a fit, to improve the model fit all items with a standardised regression weight (SRW) of less than 0.7 were deleted (El-Den et al., 2020). DM1, DM10, and DM12 were then deleted, and DM13 was left as a single-item subconstruct due to the deletion of items. An attempt was made to merge the single-item subconstruct with other theoretically relevant subconstructs to prevent model misfit due to limited reliability and content validity issues presented by single-item constructs (Sideridis et al., 2018). The SRW for DM13 when merged with DMDC, which has a better theoretical justification was 0.43 which is lower than the strict threshold of 0.7 imposed in this study. Similarly, the SRW for DM13 when it was added to the less theoretically relevant subconstruct DMDV was also below the allowed threshold at 0.41. The resulting model that was a fit to the data is represented by Figure 2, with two subconstructs digital competencies and digital value creation and seven items.

The CFA results supported a model fit for digital maturity as all four conditions were met, and the Chi-square results were insignificant (X2 = 15.46, df = 13, p-value= 0.28). This indicated that the model fit the data well because the chi-square was relatively low, the ratio between chi-square and df was less than 2 and the p-value also indicated the model results were not significantly different from the observed data (Widaman & Helm, 2023). The other conditions for a model fit were satisfied (RMSEA= 0.03 which was < 0.08, CFI= 0.99 which was > 0.9 and SRMR= 0.048 which was < 0.08). Factor loadings ranged from 0.78 and 0.83 which indicates a strong relationship between the items and the constructs (Shrestha, 2021).

For the digital competency subconstruct (DMDC), the composite reliability (CR) was 0.90 and the average variance extracted (AVE) was 0.65. The digital value creation (DMDV) subconstruct had a composite reliability (CR) of 0.80 and an average variance extracted (AVE) of 0.66. Good convergent validity is realised when the AVE for a construct is greater than 0.5 and good composite reliability is deduced when the CR is greater than 0.7 (Nasution et al., 2020). Consequently, DMDC and DMDV constructs were confirmed to have good convergent validity and composite reliability.

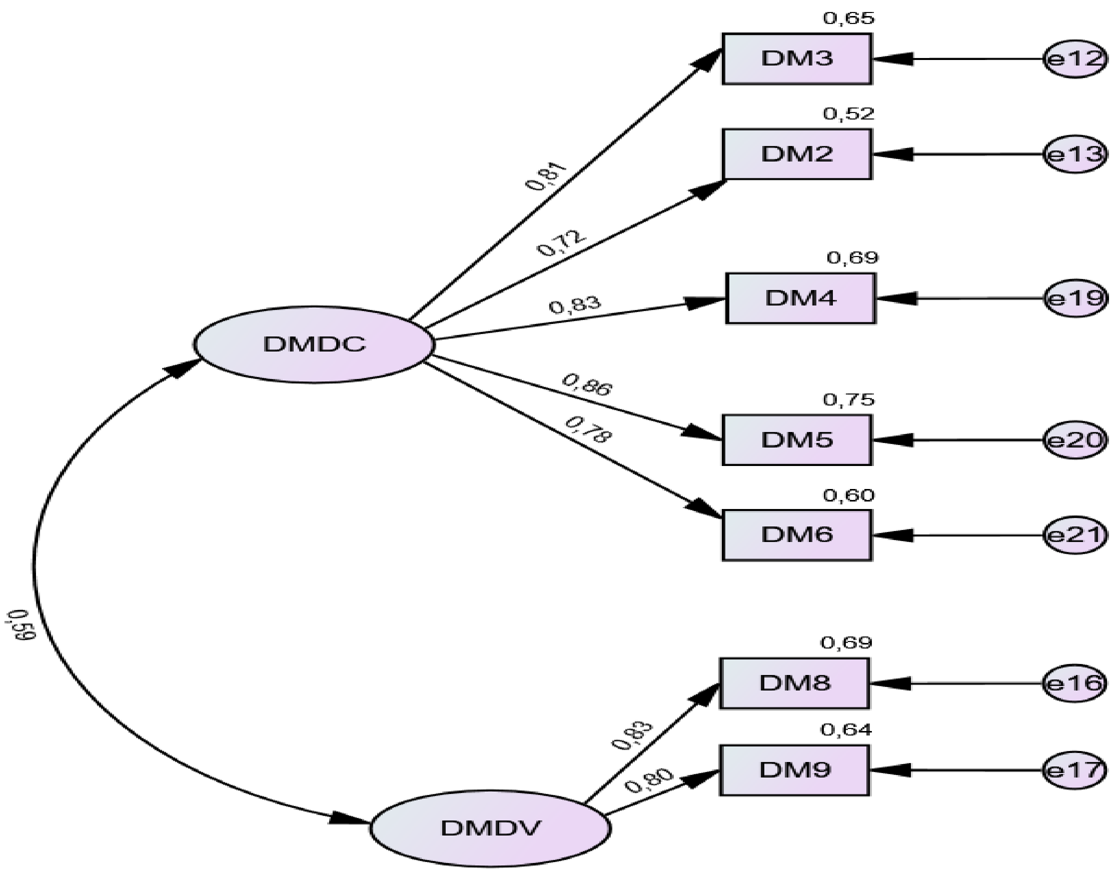

Figure 2: CFA model for digital maturity construct

5.5.2 CFA: Digital innovation

The CFA results supported the unidimensional structure of digital innovation (X2 = 0, df = 0, p-value 1.00). While this might indicate a perfect fit, it is not unusual for a unidimensional construct with just three constructs (Hu & Bentler, 1999). The factor loadings ranged from 0.68 to 0.78 which indicates a strong relationship between the items and the constructs (Shrestha, 2021). Figure 3 represents the unidimensional digital innovation subconstruct with three items. The composite reliability (CR = 0.78) and the average variance extracted (AVE = 0.54) also supported adequate construct reliability and validity.

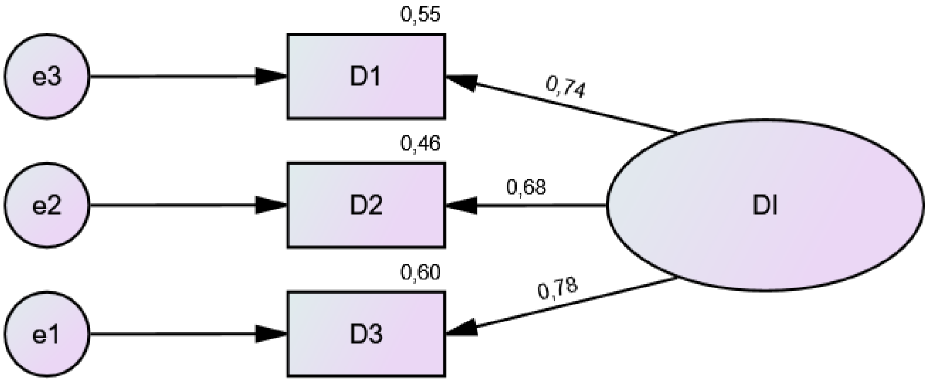

Figure 3: CFA model for digital innovation construct

5.5.3 CFA: Supply chain resilience

The initial CFA model was not a fit, to improve the model fit all items with a standardised regression weight (SRW) of less than 0.7 were deleted (El-Den et al., 2020). SCR3, SCR5, SCR11, SCR14, SCR24, SCR40, and SCR42 were then deleted, and SCR28 was left as a single-item subconstruct due to the deletion of items. An attempt was made to merge the single-item subconstruct with other theoretically relevant subconstructs to prevent model misfit due to limited reliability and content validity issues presented by single-item constructs (Sideridis et al., 2018). The SRW for SCR28 when merged with constructs with which it had a theoretical relationship were 0.57 for RDM, 0.55 for OA and then 0.51 for SCF which were lower than the strict threshold of 0.7 imposed in this study. Similarly, the SRW for SCR28 when it was added to the less theoretically relevant subconstructs MD and RA was also below the allowed threshold at 0.48 and 0.44 respectively. Consequently, SCR28 was also deleted. The resulting model that was a fit to the data is represented by Figure 4, with five subconstructs namely; Operational Agility (OA), Responsive Demand Management (RDM), Supply Chain Flexibility (SCF), Market diversification (MD) and Resource agility (RA). The final model had 12 items across the five subconstructs.

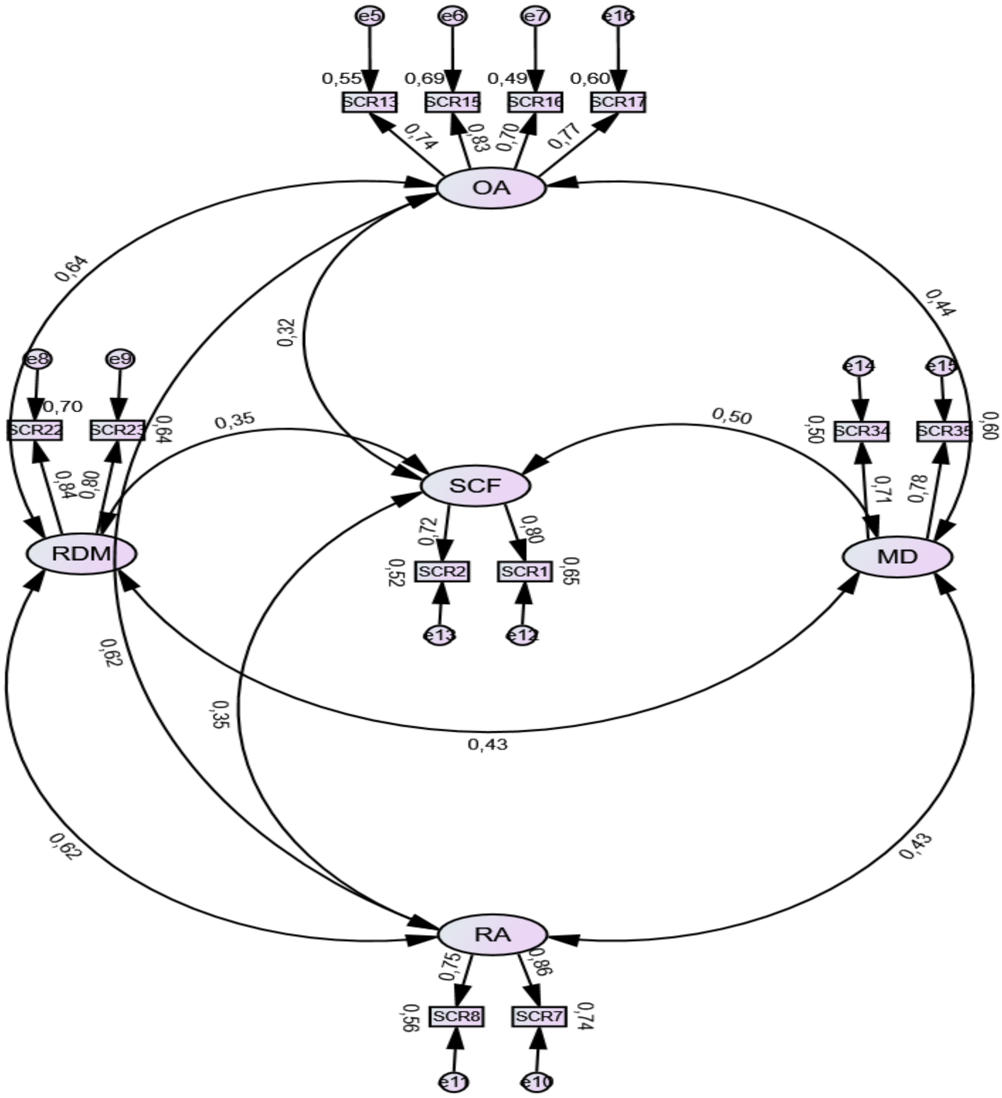

Figure 4: CFA model for supply chain resilience construct

The CFA results supported a model fit for supply chain resilience as all four conditions were met, and the Chi-square results were insignificant (X2 = 54.95, df= 45, p-value= 0.15). This indicated that the model fit the data well since the chi-square was relatively low, the ratio between chi-square and df was less than 2 and the p-value also indicated the model results were not significantly different from the observed data (Widaman & Helm, 2023). The other conditions for a model fit were satisfied (RMSEA= 0.033 which was < 0.08, CFI= 0.99 which was > 0.9 and SRMR= 0.043 which was < 0.08). Factor loadings ranged from 0.70 and 0.86 which indicates a strong relationship between the items and the constructs. Good convergent validity is realised when the AVE for a construct is greater than 0.5 and good composite reliability is deduced when the CR is greater than 0.7 (Nasution et al., 2020). Table 23 summarises the AVE and CR for each subconstruct. Consequently, all the subconstructs were confirmed to have good convergent validity and composite reliability.

Table 23. AVE and CR values for SCR subconstructs

Subconstruct	AVE	CR
OA	0.58	0.85
MD	0.56	0.71
RDM	0.67	0.81
SCF	0.59	0.74
RA	0.65	0.79

5.6 Hypothesis testing

5.6.1 Predictive quality assessment

Before hypothesis testing, a predictive analysis was done to assess the model's predictive quality. The R^2 values (the squared multiple correlations) were evaluated to check how much variance of the variance in SCR (endogenous variable) is explained by the DM (exogenous variable), higher R^2 values indicate good explanatory power and predictive relevance (Shmueli et al., 2019). R^2 values above 0.3 for the key endogenous variables (DI and SCR) indicate that the model has a good predictive quality (Shmueli et al., 2019). In this study, the R^2 values for both endogenous variables were greater than 0.3 which supported the model's good predictive quality. R^2 for DI was 0.65, which implied that DM explained 65% of the variance in DI. R^2 for SCR was also 0.65, indicating that 65% of the variance in SCR was explained by a combination of DM and DI.

Residual analysis was also done to assess the model's predictive quality. This was to check the difference between the predicted and observed values of the endogenous variables. Good predictive quality is indicated by standardised residuals that are within the ±2.5 threshold (Kline, 2015, p. 417). In this study, all the standardised residuals were within the threshold, ranging from -1.35 to 2.11, further supporting the model's predictive quality.

5.6.2 Hypothesis 1: Digital maturity positively impacts digital innovation.

The initial SEM model was not a perfect fit for the dataset, with some items having low loading factors below 0.4. SCR1, SCR2, SCR34, SCR35 and DM9 were removed due to low loading factors below 0.5. After removing the low-loading factor items, the model was still not a perfect fit although it had improved. Covariances were then added for all the modification indices (MIs) greater than 20, the resulting model was a much better fit with all the model fit indicators (RMSEA= 0.048, CFI = 0.97, SRMR= 0.058 and Chi-square/df = 1.47) supporting a good fit except the Chi-square p-value which was 0.001. This indicated some level of a model misfit; consequently, further model improvements were made by adding more covariances for MIs greater than 10. The model improved showing a better fit to the data based on the model fit indicators (RMSEA= 0.042, CFI = 0.98, SRMR= 0.051 and Chi-square/df = 1.37). The Chi-square p-value still indicated a significant difference between the model and the observed variables but improved to 0.006.

The loading factors were reviewed again, and two items (SCR22 and DM8) were identified as candidates for deletion as they were below 0.5, after deleting these the model further improved (RMSEA= 0.038, CFI = 0.99, SRMR= 0.046 and Chi-square/df = 1.29). Although the Chi-square p-value still indicated a significant difference between the model and the observed variables, it had improved to 0.037. Based on the other model fit indicators strongly supporting the model fit, and the improved p-value the model was deemed to be sufficient to test the hypothesis with. The final structural model of digital maturity and digital innovation on supply chain resilience is illustrated in Figure 5. The path DM -> DI had a path coefficient (β) of 0.81 indicating a strong positive significant relationship with a p-value < 0.001, therefore hypothesis 1 was supported by the study’s data analysis.

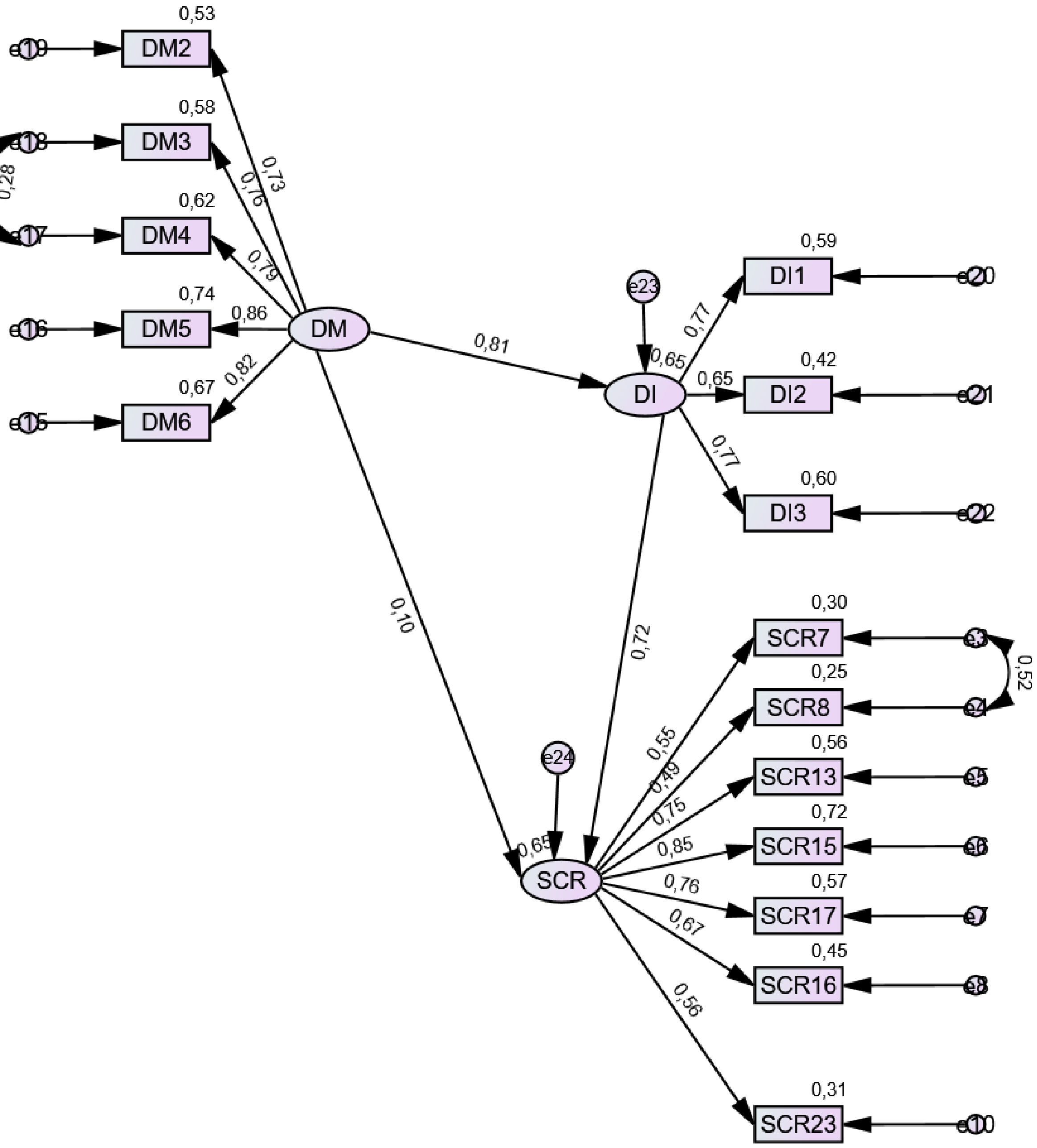

Figure 5: Final structural model of DM and DI on SCR

5.6.3 Hypothesis 2: Digital innovation has a positive influence on SCR.

The path DI -> SCR had a path coefficient (β) of 0.72 indicating a strong positive significant relationship with a p-value < 0.001, therefore hypothesis 2 was supported by the study's data analysis.

5.6.4 Hypothesis 3: The relationship between digital maturity and SCR is mediated by digital innovation.

Hypotheses 1 and 2 imply that digital maturity significantly affects digital innovation, and digital innovation significantly affects supply chain resilience. The direct path from DM -> SCR had a β value of 0.10 with a p-value of 0.46, this implied that the direct effect of digital maturity on supply chain resilience is not significant. This suggests that digital innovation fully mediates the relationship between digital maturity and supply chain resilience.

5.7 Summary of Findings

The data collected from the online survey questionnaire investigated the relationship between digital maturity and supply chain resilience as well as the mediation effect of digital innovation on this relationship. The results indicate that no direct relationship exists between digital maturity and supply chain resilience, but an indirect relationship exists in the presence of digital innovation, supporting full mediation. These results are discussed in Chapter 6, where they also are interpreted concerning their significance to the literature. Chapter 7 discusses the limitations of these results and what this means for scholars and the business fraternity, before making recommendations on areas for future studies.

CHAPTER 6 – DISCUSSION OF THE RESULTS

6.1 Introduction

This chapter discusses the results presented in Chapter 5 and compares them to the literature in Chapter 2. It also discusses the research findings' implications for theory and practice and concludes that the research findings confirm and extend the literature. Finally, a model is presented on the relationship between digital maturity, digital innovation, and supply chain resilience.

6.2 Results summary

6.2.1 Data collection and sample size

A similar study was conducted by Zouari et al. (2021), which involved evaluating the impact of the degree of digital maturity and digital adoption in the supply chain on supply chain resilience. The study sampled 300 supply chain managers in France. However, the populations of France and South Africa are comparable, between 63 and 67 million, with the manufacturing industry's contribution to the GDP of about 10% (United Nations, 2024). France’s GDP is eight times bigger than that of South Africa, this is an indicator that the number of supply chain managers in the manufacturing industry in South Africa is less than in France (World Bank, 2024).

Furthermore, this study restricted the respondents to the FMCG industry, thus excluding other SCMs from the manufacturing industry. A minimum sample of 200 participants was explored, as this is a requirement to conduct covariance-based structural equation modelling (Rahman, 2023). In total, 206 valid responses were received from 30 July 2024 until 20 September 2024, and this was deemed adequate based on sample sizes that similar studies achieved relative to the population in different geographical contexts. While the responses exceeded the minimum target, the respondents were primarily concentrated on the production function of the supply chain, as outlined in Chapter 4 of this study. This may have a negative effect on the generalisability of the study’s result. However, the data was considered representative and adequate as the FMCG manufacturing industry supply chain, like any manufacturing industry, is mainly made of production personnel with other functions acting as support functions.

6.2.2 Pilot study

Pilot studies are preliminary research investigations conducted to test, refine and validate the study's design, methods and procedures before carrying out a larger study (Moore et al., 2021). The pilot study feedback allows for validation of the study design, refining research questions and assessing the full-scale study's feasibility (Moore et al., 2021). The pilot study feedback for this study indicated issues in terms of the questionnaire, these included a high number of questions and survey completion time, spelling errors, and the absence of a way to detect duplicate responses from a single respondent. Accessibility of the online survey through various devices was confirmed as well as the readability and user-friendliness of the Microsoft Forms tool on different devices, i.e. cell phones, tablets and desktops. The survey was amended to correct the issues highlighted and was deemed adequate to be used for the data collection phase.

6.2.3 Validity and Reliability

Validity is the extent to which a research instrument measures what it is meant to measure, thereby indicating the trustworthiness of the research findings (Babbie, 1995; Welman & Kruger, 2001). Construct validity is a measure of how well the construct items describe the theoretical concept it claims to represent (Shrestha, 2021). In this study, the construct validity was evaluated and confirmed with convergent and discriminant validity. The measurement scale was also tested for reliability, which measures a measurement instrument's consistency, dependability, and accuracy (Hair et al., 2019). It evaluates the stability and repeatability of the results, and in this study, reliability was confirmed with the composite reliability and Cronbach's alpha.

6.2.4 Descriptive statistics

Sample relevance increases the confidence of the generalisability of a study's findings (Hultsch et al., 2002; Murad et al., 2018). Sample relevance is the extent to which a sample is deemed representative of the population of interest (Murad et al., 2018). In this study, the sample was deemed relevant as only valid responses were used, adhering to the experienced supply chain managers in the South African FMCG industry. Two in five of the respondents were female, and three in five of the respondents were male, further supporting sample relevance. The sample was also fairly spread between junior, middle and senior managers, although biased towards production with more than half the respondents working in that function this is not out of the ordinary as the production personnel tend to outnumber other supporting functions in the supply chain of manufacturing companies.

In addition to sample relevance, the extensiveness of the sample was also deemed sufficient as the study had 206 valid responses which is a large sample when comparing similar studies with larger populations of interest. Large samples tend to be extensive (Adhikari, 2021), and sample extensiveness refers to the extent to which a sample is representative of the diversity of its population of interest (Delice, 2010). The respondents' profiles indicate a good seniority, company size, and age spread, further making a case for sample extensiveness.

6.3 Hypothesis testing and interpretation

6.3.1 Digital maturity positively impacts digital innovation

Digital maturity is a building block for digital innovation, as without digital maturity an organisation cannot exploit digital technologies for its competitive advantage (Kohli & Melville, 2019). A study done on micro and small enterprises (MSEs) in Brazil, an emerging market, revealed that there is a positive correlation between digital maturity and innovation as well as turnover (da Costa et al., 2022). Another study on organisations in Malaysia, another emerging market, also found that the same relationship exists between the two constructs (Chandrakasan et al., 2023). Consequently, irrespective of the firm size the literature suggests that digital maturity leads to digital innovation (Chandrakasan et al., 2023; da Costa et al., 2022).

Van den Born et al. (2020) argued that organisations lacking digital maturity need to innovate rapidly during crises such as COVID-19. Rapid digital innovation tends to be riskier and has a far lower success rate than incremental digital innovation (Van den Born et al., 2020; Humaidi et al., 2023).

Furthermore, it is argued that in small and medium enterprises (SMEs) during times of crises digital maturity becomes irrelevant in the absence of entrepreneurial personality traits that moderate the relationship (Van den Born et al., 2020). SME entrepreneurs have benefitted from exploiting digital technologies to compete in markets that would otherwise be reserved for large enterprises (Chatterjee et al., 2022). SMEs are typically owner-managed and started by persons who possess entrepreneurial traits (Henschel & Heinze, 2018; Ng & Kee, 2018). It follows that the relationship between digital maturity and digital innovation in the context of SMEs during times of crisis is moderated by entrepreneurial personality traits, in the absence of which the relationship is insignificant (Van den Born et al., 2020).

The literature suggests that the relationship between digital maturity and digital innovation does not depend on firm size unless under extreme adversity (Chandrakasan et al., 2023; da Costa et al., 2022; Van den Born et al., 2020). It then begs the question, does this relationship apply in supply chains that are susceptible to disruptions due to local and global factors that are external to the organisation? Especially in a highly competitive industry like the FMCG industry, characterised by low margins and high volumes (Magagula et al., 2020; Niedermeier et al., 2021). Where disruptions to the supply chain threaten not only the market survival of the organisation but also the masses who rely on these products in their daily lives (Magagula et al., 2020).

The study investigated whether there was a significant relationship between digital maturity and digital innovation, in the context of the supply chain industry of FMCGs in South Africa. Digital maturity is a multidimensional construct, and the result of this study produced two dimensions namely digital capabilities (DMDC) and digital value creation (DMDV). The model fit output confirmed the multidimensionality nature of the two subconstructs as valid and reliable to measure digital maturity.

Digital capabilities enable an organisation to exploit digital technologies, allowing digital innovation to thrive within an organisation (Gupta et al., 2022). Organisations ought to use digital technologies to support knowledge acquisition capabilities as well as the ability to understand market dynamics to gain a competitive edge (Tortora et al., 2021). Digital technologies increase the value of internally and externally sourced information and knowledge, driving organisational collaboration efforts (Tortora et al., 2021; Source). To derive value from this, organisations must continuously acquire and implement enough dynamic capabilities to foster digital innovation (Tortora et al., 2021; Source). Digital capability has been found to lead to an organisation's digitisation, driving digital innovation and organisational performance (Benitez et al., 2022; Heredia et al., 2022). Wang et al. (2022) confirmed this relationship in the context of manufacturing companies in China.

Digital value creation within organisations is supported by the integration of digital capabilities which leads to digital innovation (Edu et al., 2020). This benefits the organisation in terms of managerial decision-making, operational activities, and alignment of information technology infrastructure driving organisational performance. A study by Di Vaio et al. (2021) emphasised the need to consider value creation and capture in the innovation process.

The descriptive statistics indicated that digital maturity was generally high, although digital value creation (DMDV) was higher than digital capabilities (DMDC) according to the respondents. The results of the SEM revealed that the two dimensions had a statistically significant positive relationship with digital innovation (DI). The results aligned with the literature, which concluded that digital capabilities positively influence organisational innovation, supporting organisational performance (Benitez et al., 2022; Heredia et al., 2022; Tortora et al., 2021). Di Vaio et al. (2021) and Edu et al. (2020) found that digital value creation drives digital innovation within organisations.

Therefore, this study finds that digital maturity positively influences supply chain resilience in South Africa, an emerging market with a highly competitive and saturated FMCG industry.

6.3.2 Digital innovation has a positive influence on supply chain resilience

Digital innovation allows organisations to adopt, generate and recombine digital technologies to adapt their business models and capacity to be adaptive to satisfy supply chain resilience (Felicetti et al., 2024). Digital innovation can disrupt organisations and industries influencing organisational decision-making and capabilities, which when possessed aids the transformative capacity of organisations (Ghosh et al., 2022). Digital innovation enhances knowledge management systems to drive information flow and visibility through data analytical tools communication assistance, knowledge transfer and proactive risk management practices (Di Vaio et al., 2021). Furthermore, digital innovation enhances the capabilities that are necessary ingredients in resilient supply chains allowing the supply chain system to withstand the effects of disruptions before the system control or structure is affected (Mukherjee et al., 2024; Revilla et al., 2024; Wieland & Durach, 2021).

The study also investigated whether there was a significant relationship between digital innovation and supply chain resilience. It examined the construct using a three-item scale, unsurprisingly yielding a unidimensional structure. The model fit output confirmed the one-dimensionality of digital innovation as valid and reliable, showing a perfect fit to the data, which is expected of unidimensional constructs (Dunn & McCray, 2020).

The descriptive statistics indicated that digital innovation was generally high. The results of the SEM revealed that digital innovation had a statistically significant positive relationship with supply chain resilience. The results were in alignment with the literature which suggests that digital innovation allows organisations to develop resilience in their supply chain (Nakandala et al., 2023). Digital innovation allows organisations to transform their business model to build organisational resilience (Heinz et al., 2021; Schaffer et al., 2021). Emerging literature has focused on how resilient organisations are those that recover quickly and respond more rapidly, it is argued that this is achieved through mindfulness which is enabled by digital innovation (Ye et al., 2024).

Therefore, this study finds that digital innovation positively influences supply chain resilience in South Africa, an emerging market with a highly competitive and saturated FMCG industry.

6.3.3 The relationship between digital maturity and supply chain resilience is mediated by digital innovation

A study done by Zouari et al. (2021) with supply chain managers in France found that the degree of digital maturity positively influences supply chain resilience. The study indicated that this relationship exists in companies of different sizes. Another study done on port firms in China found that technological innovation positively mediates the relationship between digital transformation and SCR (He et al., 2023). Digital transformation requires digital maturity for it to be effective (Mugge et al., 2020), consequently there is a case to be made for digital innovation mediating the relationship between digital maturity and supply chain resilience.

This study aimed to establish if this applies to the FMCG industry, which is characterised by high volumes, low profit margins, and a competitive landscape within the context of South Africa, an emerging market. Furthermore, it sought to determine if digital innovation mediated the relationship given the high level of competitiveness driven by the need for significant market share for market survival (Magagula et al., 2020).

The study investigated the mediation of digital innovation on the relationship between digital maturity and supply chain resilience in the South African FMCG industry. There is a lack of consensus in the literature on the conceptualisation of supply chain resilience (Han et al., 2020; Li et al., 2017; Rahman et al., 2022b). The most elaborate model in the literature was used in this study (Zouari et al., 2021). Supply chain resilience is a multidimensional construct (Han et al., 2020), and the results of this study produced five dimensions: operational agility (SCR-OA), market diversification (SCR-MD), supply chain flexibility (SCR-SCF), responsive demand management (SCR-RDM), and resource agility (SCR-RA).

According to the literature, there are three dimensions of resilience, inspired by the dynamic capability and resource-based theory: readiness, response and recovery (Han et al., 2020; Li et al., 2017; Rahman et al., 2022b). The five subconstructs can be classified into these literature-derived dimensions. Operational and resource agility can be classified as representing the readiness aspect of the supply chain resilience construct as they talk to the readiness to adapt to operational changes and the ability to rapidly mobile and reallocate resources (Jermsittiparsert, 2022). Responsive demand management and supply chain flexibility represent the response aspect of the supply chain resilience construct. They talk about the ability to adjust supply chain operations in real time to effectively react to changes in customer demand and other immediate circumstances (Kamalahmadi et al., 2022). Market diversification represents the recovery aspect of the supply chain resilience construct as it is a strategy through which growth and stability can be achieved after a disruption by exploring new markets, products or services (Lin et al., 2021). The model fit confirmed the multidimensionality of the five subconstructs as valid and reliable measures of supply chain resilience.

The descriptive statistics indicated that supply chain resilience was generally high, although supply chain flexibility (SCR-SCF) and market diversification (SCR-MD) were higher, according to the respondents. In the final structure model after removing low-loading factor items and adding covariances for modification indices less than 10, supply chain resilience had three subconstructs namely operational agility (SCR-OA), responsive demand management (SCR-RDM), and resource agility (SCR-RA). Queiroz et al. (2022) posit that in an emerging market context, the most important dimensions of supply chain resilience are supply chain flexibility and resource agility during huge disruption scenarios such as COVID-19. Other dimensions of supply chain resilience in the literature are economic viability, social equity, communication and information flow, infrastructure, governance and decision-making, analysed in the context of food supply chains (Hecht et al., 2019; Li et al., 2023). Transparency and visibility, flexibility and adaptability, risk management, collaboration and coordination, innovation and technology are other dimensions found in the literature (Kazancoglu et al., 2021; Ruiz-Alba et al., 2023). However, scholars do not agree on a set of dimensions that describe the supply chain resilience construct (Hecht et al., 2019; Li et al., 2023; Queiroz et al., 2022). The existing dimensions in the literature mostly relate to readiness, responsiveness, and recovery as the key ingredients of the supply chain resilience dimensions as supported by the dynamic capabilities theory and resource-based theory (Han et al., 2020; Li et al., 2017; Rahman et al., 2022b).

The results of the SEM revealed that the direct effect of digital maturity on supply chain resilience was statistically non-significant, while the indirect effect was statistically significant through digital innovation. The results of this study suggest that in the context of a developing market and the FMCG industry, digital innovation fully mediates the relationship between digital maturity and supply chain resilience. Zouari et al. (2021) conducted a study in France, a developed market with supply chain managers across various industries and found that a degree of digital maturity leads to supply chain resilience irrespective of company turnover. However, the relationship was found to be stronger for companies with lower turnovers.

Robertson et al. (2022) conducted a study to confirm the positive relationship between digital maturity and supply chain resilience, in South Africa during the COVID-19 pandemic in SMEs. This study's findings suggest that this relationship does not exist in the context of South Africa, an emerging market and the FMCG industry unless mediated by digital innovation. Consequently, a fourth hypothesis was introduced to understand if company size impacts the relationship between digital maturity and supply chain resilience in the context of the South African FMCG industry.

Hypothesis 4: The relationship between digital maturity and supply chain resilience depends on company size.

6.3.4 The impact of company size on the relationship between digital maturity and supply chain resilience.

To test hypothesis 4, a regression analysis was conducted between the dependent variable, supply chain resilience and the independent variables, company size and the interaction term. Regression analysis is a statistical technique to evaluate the relationship between one dependent variable and one or more independent variables (Alita et al., 2021). Multiple regression analysis allows for quantifying relationships with multiple predictors and can include interaction terms to investigate more complex relationships (Kelley & Bolin, 2013). In this study, multiple regression analysis helped in understanding how changes in company size affected its supply chain resilience and was, therefore, the method of choice for testing hypothesis 4 (Alita et al., 2021; Kelley & Bolin, 2013).

An interaction term was included in the analysis to enable exploration of the complex relationship between company size, digital maturity and supply chain resilience (Kelley & Bolin,2003; Moody et al., 2017). The interaction term was created by multiplying company size with digital maturity; this allowed for the evaluation of the impact of digital maturity on supply chain resilience at various company sizes. Table 24 summarises the model results for the regression analysis of the impact of company size and interaction effects on supply chain resilience. This study categorised small enterprises as companies with less than 500 employees and large enterprises with more than 500 employees.

Table 24: Multiple regression model out for testing hypothesis 4

Model statistics	Model output	Significance (p-value)
R^2	0.39	
F-statistic	$F(2, 203) = 65.51$	< 0.001
Company size β value	-1.39	< 0.001
Interaction β value	0.33	< 0.001

The assumptions for multiple regression, which were linearity, independence, normality, absence of multicollinearity, and homoscedasticity, were already checked and confirmed as multiple regression shares similar assumptions with SEM (Kelley & Bolin, 2013). The R square value of 0.39 indicated that the model could explain 39% of the variance in the dependent variable, supply chain resilience, which includes company size and the interaction term. This suggests a moderate relationship, which is indicative that other factors not included in the model may influence supply chain resilience. In this study, company age is an example of such a factor.

The overall model was significant as indicated by the F-statistic of $F(2,203)$ with a p-value of < 0.001, which implied that at least one of the model predictors, i.e. company size and the interaction term, contributes to explaining the dependent variable, supply chain resilience. The negative coefficient for company size of -1.39 with a p-value of < 0.001 suggests a significant and inverse relationship between company size and supply chain resilience (Alita et al., 2021). That is, as company size increases, supply chain resilience decreases. The interaction term was also significant, with a p-value of < 0.001 and a positive coefficient of 0.33, indicating that the impact of digital maturity on supply chain resilience varies depending on company size. Consequently, hypothesis 4 was supported. The relationship between digital maturity and supply chain resilience depends on company size.

In this study, over 76% of the respondents worked for larger enterprises that cannot be classified as SMEs. This explains the deviation from the literature implied by the findings of this study. The data collected in this study is representative of large enterprises. Digital technologies require investments which disadvantages smaller enterprises when it comes to being digitally innovative (Telukdarie et al., 2023). However, they tend to have leaner structures and are more adaptive, supporting faster decision making driving their business model innovation in the digital era (Andersen et al., 2022). On the other hand, digitally mature SMEs are likely to maximise the potential of existing digital technologies that they have invested in (Williams & Schallmo, 2020). Bigger organisations are often complex with bureaucratic structures but with a larger scale and scope (Müller et al., 2021), this can support the need to be digitally innovative to be able to sustain and grow market share, especially in a typically saturated and highly competitive industry such as the FMCG industry (Magagula et al., 2020; Niedermeier et al., 2021).

Therefore, a comparison of the results of this study with the literature has two main findings. Firstly, the direct and positive relationship established in the literature on digital maturity and supply chain resilience is not supported by this study as it was either done with SMEs or in developed markets (He et al., 2023; Zouari et al., 2021). Even the study done in South Africa by Robertson et al. (2022) was done within the SME sector. Secondly, the study by Zouari et al. (2021) supported the direct relationship between digital maturity and supply chain resilience; they did note that it was stronger with smaller enterprises. Furthermore, it was conducted in a developed market and did not account for the impact of industry type on the relationship.

Therefore, this study finds that in the context of South Africa, an emerging market, and the highly competitive and saturated FMCG industry digital maturity has no direct relationship with supply chain resilience. However, the relationship is fully mediated by digital innovation. Furthermore, it finds that the relationship between digital maturity and supply chain resilience is moderated by company size.

6.3.5 The final model of the study

This research confirms the resource-based theory in that investment in digital technologies to build digitally mature organisations creates resources that are valuable, rare, and inimitable (Cuthbertson et al., 2022; Elia et al., 2021). These resources enable the organisation to develop new capabilities, creating an environment where digital innovation can thrive (Chirumalla, 2021). This gives an organisation a competitive edge over its competitors (Cuthbertson et al., 2022; Elia et al., 2021), which is a necessary ingredient for longevity and resilience in a highly competitive industry such as the FMCG industry (Niedermeier et al., 2021).

The research also confirms the dynamic capabilities theory view that organisations should strive for continuous improvement using their resources and capabilities (Chirumalla, 2021). To do this, resources and capabilities should continuously be integrated, reconfigured and transformed to be able to react and adapt to changing market conditions (Bergami et al., 2022). This is important in a business world that is characterised by vulnerability, uncertainty, complexity and ambiguity (VUCA) that organisations need to manoeuvre (Jermsittiparsert, 2022). In the VUCA world, there is rapid technological advancement and increased competition (Grzybowska & Tubis, 2022). It thus follows that digital innovation is key to ensuring that the supply chain organisations manage disruptions in the most efficient way possible as allowed by its digital capabilities and resources (Ambrogio et al., 2022).

Figure 6 represents the final model of the study. It has three main constructs: digital maturity, digital innovation, and supply chain resilience. Digital maturity has two subconstructs: digital capabilities and digital value creation. Digital innovation is a unidimensional construct. Based on the final structure of the model, supply chain resilience has three subconstructs: operational agility, responsive demand management, and resource agility.

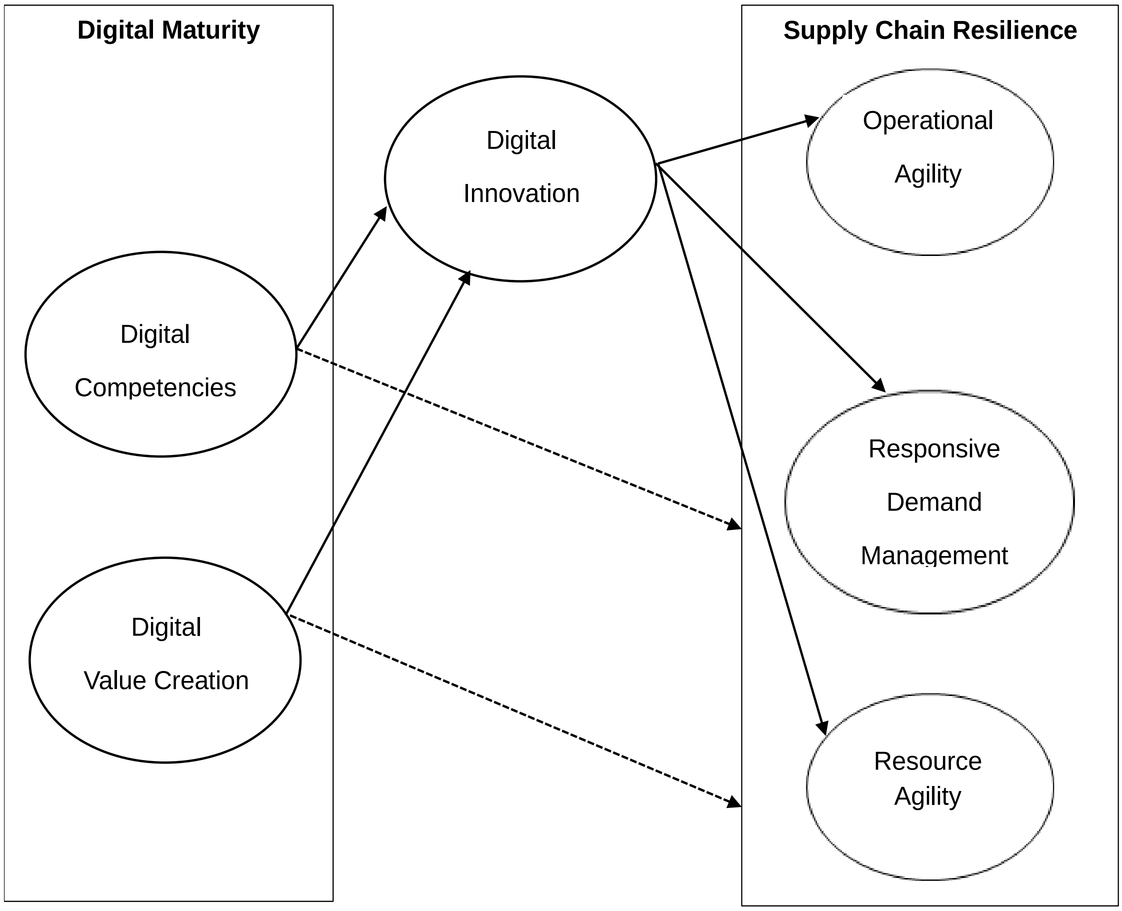

Figure 6. The final model of the study

The model fit results confirmed the multidimensionality of the four subconstructs to measure supply chain resilience, the two subconstructs to measure digital maturity and the one-dimensionality of digital innovation. The existence of digital maturity does not necessarily result in digital innovation, as some organisations might choose to focus on leveraging their digital capabilities on their existing processes and not pursue new opportunities (Khin & Ho, 2019; Yasa et al., 2019). However, the positive influence digital maturity has on digital innovation is sufficient to motivate organisations to strive for high levels of digital maturity if they are to be digitally innovative (Khin & Ho, 2019; Yasa et al., 2019). This supports the use of the resource-based theory and dynamic capabilities theory in this study, as the continuous integration, reconfiguration and transformation of resources and capabilities are the backbone of supply chain resilience in highly competitive industries operating in VUCA environments (Bergami et al., 2022; Jermsittiparsert, 2022).

Given the nature of the FMCG industry in South Africa, that is characterised by high competition, high volume and low-margin products, global supply chains and a saturated market (Magagula et al., 2020). It follows that to achieve supply chain resilience in this context an organisation would need more than just digital maturity but to continuously improve, integrate, transform and reconfigure its resources and capabilities thereby promoting digital innovation (Cuthbertson et al., 2022; Elia et al., 2021; Chirumalla, 2021). This would give it the ability to attain operational and resource agility, enabling its supply chain to rapidly respond to demand in the face of disruption.

6.4 Conclusion

The purpose of the research study was to evaluate the impact of the use of digital technologies by South African FMCG manufacturing companies on their ability to deal with supply chain disturbances. The research confirmed all the hypotheses. What was interesting was the effect of company size, industry, and market type on the mediation effect of digital innovation on digital maturity and supply chain resilience. This study confirms the literature that digital maturity has a positive effect on digital innovation and that digital innovation positively influences supply chain resilience. It extends the literature by establishing that the direct relationship between digital maturity and supply chain resilience does not hold for all company sizes and possibly industry type and company age.

In this chapter, the results presented in Chapter 5 were discussed and interpreted. The validity and reliability of the results were covered, as well as the implications of data collection procedures, sample size, and pilot testing. Finally, hypothesis testing was discussed, a final model for the study was introduced, and the implications of the theories underpinning this study. Chapter 7 which follows, discusses the main findings and makes recommendations for future studies. Furthermore, implications for scholars, the FMCG industry and supply chain professionals are also discussed.

CHAPTER 7 – CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

In this chapter, a summary of the main findings is provided as well as a discussion of the implications of the study for various stakeholders which includes supply chain managers, FMCG manufacturing businesses, and government. Additionally, the implications of this research for scholars as well as the limitations of the study are also discussed. Recommendations are then made on possible areas for future research in the digitalisation and supply chain resilience of the manufacturing sector. Conclusions are then drawn on the importance of the study and its contribution to academia and the business world.

7.2 Summary of the main findings

This study, built on the work of Zouari et al. (2021) as their instrument, was used in the empirical investigation of the relationship between digital maturity and its sub-constructs, digital competency and digital value creation, as well as supply chain resilience and its related subconstructs. The instrument possesses the most extensive measure of supply chain resilience in literature (Zouari et al., 2021). The literature has no consensus on the dimensions that describe supply chain resilience (Han et al., 2020; Li et al., 2017; Rahman et al., 2022b).

The study's initial model had eight subconstructs, and the final model yielded three subconstructs: operational agility, responsive demand management, and resource agility. Del Giudice et al. (2021) work was also used to understand the mediation role of the digital innovation construct on the relationship between digital maturity and supply chain resilience, as their study also focused on the digital innovation construct.

The context of the study by Del Giudice et al. (2021) involved supply chain managers in SMEs in Italy, a developed country and the manufacturing industry, in particular the furnishing, machinery and automobile industries. Zourari et al. (2021) also focused on supply chain managers, but in France, another developed country across various industries. This study explored the relationship between digital maturity, digital innovation and supply chain resilience in South Africa, an emerging market and the FMCG industry, which is highly competitive and saturated (Magagula et al., 2020).

The focus and context of this study are important as emerging markets are lagging when it comes to digitisation and level of digital maturity (Kohli & Melville, 2019). Global supply chain disruptions due to factors such as geopolitics and pandemics render today's business environment as volatile, uncertain, complex and ambiguous (Ali et al., 2021; Jermsittiparsert, 2022; Ponomarenko & Rasshyvalov, 2023). Digitisation has also disrupted many industries due to digital innovation which drives business model innovation and organisational performance by giving organisations a competitive edge (Ancillai et al., 2023; Kohli & Melville, 2019). To ensure sustainable business performance, supply chain resilience is essential for manufacturing companies and businesses in general (Martínez-Caro et al., 2020).

The FMCG industry is characterised by high volumes and low margins of products, and it is highly competitive (George & George, 2023; Niedermeier et al., 2021). In the context of South Africa, it is highly saturated and contributes 20% of the country's GDP employing over a million people (Magagula et al., 2020; Statistics South Africa, 2022). South Africa has a relatively high unemployment rate (Francis et al., 2020) and the nature of the FMCG industry requires resilient supply chains to ensure consistent supply to sustain and grow market share (Niedermeier et al., 2021). Consequently, it was essential to understand the relationship between digital maturity and supply chain resilience as well as the mediation effect of digital innovation in the context of South Africa's FMCG industry.

The study's findings were as follows:

- The study revealed that digital maturity positively influences digital innovation, irrespective of company size in the context of South Africa's FMCG industry. Similarly, it was found that digital innovation leads to higher levels of supply chain resilience within organisations in the same context. Additionally, it was established that the existence of digital maturity does not necessarily translate into supply chain resilience but is driven by the act of exploiting and integrating digital technologies to create new and improved business processes, products and services known as digital innovation.

- The study also found that the relationship between digital maturity and supply chain resilience is moderated by company size. In this study, most of the respondents worked in relatively large enterprises. This explained the deviation from the literature, which suggested a direct relationship between digital maturity and supply chain resilience (Robertson et al., 2022; Zourari et al., 2021). The study found that the literature had not considered industry type and company size in this relationship in the context of an emerging market.

- The nature of the FMCG industry in terms of competitiveness, market saturation in a South African context and the need for consistently high volumes as a consequence of low margins (George & George, 2023; Niedermeier et al., 2021), makes this context unique. Supply chain disruptions in this industry threaten an organisation's market share and long-term financial performance, as any product stock-outs will lead to consumers trying out other available products and some may switch forever leading to a loss of market share and future profits (Eltawy et al., 2021).
- This study's sample was comprised mainly of respondents working for large enterprises and not small and medium enterprises (SMEs). SMEs are characterised by a lean structure and are typically owner-led which allows for quicker decision-making (Andersen et al., 2022), furthermore, these owners are typically entrepreneurial, and the literature suggests it is this entrepreneurial personality trait that moderates the relationship between digital maturity and supply chain resilience within SMEs in times of crises (Van den Born et al., 2020). It is argued that these are probably the contributing factors to why this study's findings found that no direct relationship between digital maturity and supply chain resilience exists. However, it is mediated by digital innovation, and company size plays a moderating role.

- Additionally, this study found that emerging markets are unique and differ from developed markets in terms of the relationship between digital maturity and supply chain resilience. It is argued that emerging markets are challenged by financial constraints, which contribute to limited digital infrastructure and variable digital skills (James, 2021). Emerging markets are also characterised by developing regulatory environments and are high-risk environments, increasing the business environment’s volatility, uncertainty, complexity, and ambiguity (Aly, 2020).

In summary, the findings of this study addressed the research questions by establishing that organisations in the FMCG industry and the context of an emerging market with high digital maturity in the absence of digital innovation do not necessarily possess supply chain resilience. Additionally, it was established that the direct relationship between digital maturity and supply chain resilience is also moderated by company size, which is stronger amongst smaller than larger enterprises.

7.3 Contribution to Theory

This study addresses the gap identified in the literature by Ghobakhloo et al. (2023), that the impact of digitisation on supply chain resilience in emerging markets is not fully understood. This was supported by Weerabahu et al. (2023) who found that there was limited literature on understanding the relationship between digitisation and the supply chain's capabilities in different geographical contexts and industries. This study contributed to the literature by investigating the impact of digital maturity and digital innovation on supply chain resilience in an emerging market context within the FMCG industry.

The study confirmed the direct relationship between digital maturity and digital innovation in this geographical and industry-type context of interest, furthermore, it confirmed another direct relationship between digital innovation and supply chain resilience. However, the study extended the literature by establishing that a direct relationship between digital maturity and supply chain resilience is moderated by company size and mediated by digital innovation. Previous studies have concluded a direct relationship between digital maturity and supply chain resilience (Robertson et al., 2022; Zourari et al., 2021).

Furthermore, Zouari et al. (2021) postulated that the relationship between digital maturity and supply chain resilience is independent of company turnover. However, they noted that the relationship is stronger for smaller companies with lower turnovers indicating some moderation activity. This study contributes to the literature by establishing that the relationship between digital maturity and supply chain resilience is complex with several moderators and mediators that scholars must fully explore.

Various studies postulated that there is a lack of consensus in the literature on the conceptualisation of supply chain resilience (Han et al., 2020; Li et al., 2017; Rahman et al., 2022b). This study found that the most important dimensions of supply chain resilience in the context of an emerging market and the FMCG industry are operational agility, responsive demand management, and resource agility. This adds to the body of knowledge in understanding the most important dimensions of supply chain resilience in different geographical and industry-type contexts.

The hypotheses tested in this study were derived from existing literature on the constructs, resource-based view theory, and dynamic capabilities theory. This study adds to the body of knowledge by enhancing our understanding of digital maturity and innovation as strategic resources and capabilities within organisations and how they contribute towards supply chain resilience (Ferreira et al., 2022; Gupta et al., 2020). The application of the resource-based view theory is strengthened by the link established between resources (digital maturity) and competitive outcomes (digital innovation). The applicability of the dynamic capabilities theory is established by demonstrating how digital resource configuration through digital innovation (a dynamic capability) influences resilience in today's volatile, uncertain, complex and ambiguous environment.

7.4 Implications and recommendations for relevant stakeholders

The stakeholders identified in this study included management in the FMCG industry, not limited to supply chain managers. Small and medium enterprises (SMEs), FMCG industry investors, government, and policymakers in emerging markets.

7.4.1 Management in the FMCG industry

The findings of this study highlight the important role of digital maturity and innovation in enhancing supply chain resilience. Managers should therefore prioritise and continuously invest in digital capabilities, especially in a dynamic industry such as the FMCG industry. This would build digital maturity which has been shown to improve digital innovation capabilities (Kohli & Melville, 2019). This study found that digital maturity drives innovation, enhancing supply chain resilience. The findings also suggest that the company size moderates the direct relationship between digital maturity and supply chain resilience, therefore managers should tailor digitalisation strategies according to the specific scale and capabilities of the organisation.

Today's business environment is characterised by interconnected global supply chains which increase the uncertainty and complexity of doing business (Ali et al., 2021; Jermsittiparsert, 2022; Ponomarenko & Rasshyvalov, 2023). Organisations in emerging markets have been lagging in terms of digital maturity and digital innovation (Kohli & Melville, 2019). This was apparent during the COVID-19 pandemic when organisations in developed countries were more resilient and recovered by leveraging digital technologies (Mishrif & Khan, 2023). Consequently, it is vital for managers in the FMCG industry especially in emerging markets like South Africa to strategically focus on digital maturity. Managers should implement a strategic roadmap for digital transformation to ensure that the organisation becomes and remains innovative and that its supply chain displays resilience when faced with disruptions.

Managers should also focus on creating an environment conducive to innovation across the organisation, to ensure that the organisation's digital technologies adopted are leveraged to improve the supply chain's adaptability to disruptions. This is important as the findings of the study highlight that without digital innovation, a high level of digital maturity does not necessarily translate into supply chain resilience for bigger organisations in South Africa's FMCG industry.

The mediation role of digital innovation necessitates cross-functional collaboration for digital innovation to thrive in an organisation (Appio et al., 2021). Consequently, managers should encourage and reward collaboration across functions to ensure that the development of digital maturity that an organisation invests in translates into innovation across the entire supply chain.

7.4.2 SMEs in the FMCG industry

The study confirmed the literature in that digital maturity fosters digital innovation and digital innovation drives supply chain resilience for SMEs. Furthermore, the findings supported a stronger positive and direct relationship between digital maturity and supply chain resilience as suggested by the literature (Del Giudice et al., 2021; Robertson et al., 2022). SMEs are typically resource-constrained, but digital technologies have enabled SMEs to compete in markets that would have otherwise been nearly impossible for them (Telukdarie et al., 2023). Consequently, SMEs in general including those in the FMCG industry should adopt more targeted and tailored strategies focusing on cost-effective but scalable digital solutions for future growth prospects. Examples of scalable digital solutions include big data analytics platforms, automation tools and cloud-based supply chain management systems (Felsberger et al., 2022; Iftikhar et al., 2024; Pozzi et al., 2023).

SMEs have an inherent ability for quick adoption and flexibility due to their leaner structure, making them more flexible to respond to disruptions (Andersen et al., 2022). Additionally, SMEs are typically self-managed by entrepreneurial owners, and it is argued in the literature that entrepreneurial activity moderates the relationship between digital maturity and supply chain resilience (Van den Born et al., 2020). This supports the stronger relationship that exists between digital maturity and supply chain resilience within SMEs (Van den Born et al., 2020). SMEs have to be careful as they scale because as the organisation grows the owner-driven entrepreneurial activity tends to get diluted (Olivari, 2016). Therefore, SMEs need to ensure that as the organisation grows, it does so with an innovation mindset to sustain the supply chain resilience.

Given that SMEs are resource-constrained, it is also recommended that they collaborate and form strategic partnerships with technology providers, government-supported innovation hubs, or other organisations in their industry to leverage the opportunities presented by digital technologies effectively.

7.4.3 Investors in the FMCG industry

Regarding investment potential, the study's findings indicate that organisations with high digital maturity and digital innovation tend to have better supply chain resilience, making them ideal for long-term investment. The findings of this study further indicate that investors should consider a company’s digital capabilities and size when evaluating its ability to withstand market disruptions. Applying the theory of dynamic capabilities to this context, it can be argued that organisations with the ability to reconfigure and transform their resources are better able to perform in uncertain environments (Bergami et al., 2022). Therefore, investors should value a company based on a strong base of digital assets and its agility to be innovative and adaptive. These companies are more likely to sustainably grow and manage the market and supply chain risks better (Jermsittiparsert, 2022).

7.4.4 Governments and policymakers in emerging markets

Organisations in emerging markets lag with digitisation and digital maturity, losing out on its potential benefits (Kohli & Melville, 2019). In South Africa, the contribution of industries such as the FMCG industry to the GDP is significant, at about 20% (Statistics South Africa, 2022). It also employs over 1 million people across the entire value chain (Statistics South Africa, 2023), South Africa has one of the highest unemployment rates in the world (Francis et al., 2020). Consequently, it is in the government's and the nation's best interest to support industries such as these to thrive. Digital maturity and innovation enhance supply chain resilience and organisational performance (Thordsen et al., 2020; Wagire et al., 2021). Lack of digital infrastructure and digital skills are cited as some of the barriers to digital transformation in emerging markets, government can help through funding of digital infrastructure and support for education programs involving digital transformation.

Furthermore, the government and policymakers should focus on SMEs. Unemployment is among the highest globally in an emerging market like South Africa. SMEs are a strategic sector for the government as they can collectively create more jobs for locals, tackling the issue of high unemployment rates (Abisuga-Oyekunle et al., 2020). This should be done through targeted financial incentives such as tax reliefs, low-interest loans, and grants to enable SMEs to invest in digital technologies.

The government should drive public-private partnerships and encourage collaborative efforts between government, industries, and academic institutions to help scale digital transformation initiatives faster and promote digital innovation across sectors.

7.5 Limitations of the study

Chapter 4 identified and summarised methodological limitations, but other limitations could have impacted the study's outcome.

While this study contributes to the body of knowledge about the relationship between digital maturity, digital innovation and supply chain resilience, its generalisability is limited due to the focus on the FMCG industry. Additionally, most respondents were from the production management function, although not surprising due to the relative sizes of supply chain functions within FMCG manufacturing companies. This could also affect the generalisability of the findings for the entire FMCG supply chain industry. The geographical context of the study was limited to South Africa, an emerging market. However, the findings of this study may not necessarily extend to other emerging markets.

The conceptualisation of digital innovation was limited, with a three-item instrument used in this study. This yielded a unidimensional construct, which may not be true when other extensive instruments are deployed. Furthermore, the study did not initially account for possible moderator variables until the introduction of Hypothesis 4, when company size was identified as such.

Another limitation of this study is that it was strictly a cross-sectional quantitative study. A mixed-method longitudinal study may offer an in-depth understanding of the relationship between digital maturity and supply chain resilience and the impact of mediation and moderation factors on the relationship.

7.6 Recommendations for future research

Due to the scarcity of literature on digitisation and its impact on supply chain resilience across geographical contexts (Weerabahu et al., 2023), this study should be replicated in other emerging markets. Furthermore, the relevance of this study's findings should be verified within other industries in South Africa and other emerging markets.

It is also recommended that future research focus on the impact of moderators, such as company age, on the relationship between digital maturity and supply chain resilience. Because scholars do not have a consensus on the most critical dimensions of supply chain resilience (Han et al., 2020; Li et al., 2017; Rahman et al., 2022b), more research should be done to better conceptualise the supply chain construct under different context for better practical application in industry. Conducting a mixed method and longitudinal study may offer more insight into the relationship between digital maturity and supply chain resilience and an understanding of the mediators and moderators in various contexts.

7.7 Conclusion

In conclusion, this study emphasised the critical role of digital maturity in driving supply chain resilience, with the emergence of digital innovation as a critical mediator while company size moderates this relationship. The findings of this study provide a basis for organisations to direct investments in digital technologies to help navigate disruptions to supply chains in complex and uncertain environments. While limitations exist, this study contributes to the body of knowledge in the field of digital supply chain management and the impact of company size and innovation capacity on resilience amid disruptions.

As businesses in the fast-paced FMCG industry face disruptions that render the business environment volatile and uncertain, this study offers valuable insight that can guide management in navigating this environment. Additionally, this study encourages policymakers and the government to collaborate and support sectors such as SMEs to drive economic growth and job creation. Ultimately, embracing digital maturity and innovation is no longer a choice but a transformation imperative. Organisations must be adaptive to thrive in today's rapidly evolving and uncertain business landscape.

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APPENDICES

Appendix 1: Survey questionnaire

This section outlines the survey questionnaire draft derived from the work of Zouari et al. (2021) and Del Giudice et al. (2021).

I am currently a student at the University of Pretoria's Gordon Institute of Business Science and completing my research in partial fulfilment of an MBA. I am conducting research on the impact of digital maturity and digital innovation on supply chain resilience in the South African FMCG industry**.** To that end, you are asked to complete a questionnaire survey. This will help us better understand the relationship between digital maturity, digital innovation, and SCR in the context of the South African FMCG industry and should take no more than 20 minutes of your time. Your participation is voluntary, and you can withdraw at any time without penalty. Your participation is anonymous and only aggregated data was reported. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please contact my supervisor or me. Our details are provided below:

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The following questions was on a five-point Likert scale with strongly disagree, disagree, neutral, agree and strongly disagree as the Likert scale descriptions.

Control variables and exclusion criteria

1. Role (Do you work in a supply chain? If no, do not proceed, and if yes, then continue)
2. Number of years of experience (Do you have a minimum of 5 years of experience, if no do not proceed and if yes, then continue)
3. Seniority (Junior, Middle management, Senior management, Executive)
4. Industry sector (Production, Quality assurance, Planning, Procurement, Warehouse, Route to market and Customer service were the only supply chain departments that were surveyed)

Digital maturity

Competences:

1. SCM team has skills for digital transformation.
2. SCM team has a digital mindset.
3. We rely on partners' digital skills.
4. We rely on partners' digital mindset.
5. We provide digital training for SCM.

Governance:

1. We have a leader for digital SC transformation.
2. We have processes for managing digital programs.
3. We have a digital program agenda.
4. We allocate resources for the digital SC program.
5. We understand advanced digital SC tools.

Value Creation:

1. We have a leader for digital SC transformation.
2. Data allows "pay per use" models.
3. Data helps manage returns.
4. Data helps manage orders.
5. Data helps manage maintenance.

Connectivity:

1. We have tools for data sharing.
2. We ensure information security.
3. We support data-driven processes.

Digital innovation

1. We use big data, IoT for innovation.
2. We use classroom technology.
3. We employ digital tech for new ideas.

Supply Chain Resilience

Flexibility in Sourcing:

1. Supplies used in multiple products.
2. Products have modular designs.
3. Products made on various machines.
4. Supply contracts are flexible.
5. We have alternative sources.

Flexibility in Order Fulfilment:

1. We vary outsourced services quickly.
2. We delay production as needed.
3. We pool inventory centrally.
4. We have advanced inventory management.
5. We change shipment routes quickly.
6. We reallocate orders and jobs.

Capacity:

1. We have reliable backup utilities.
2. We access redundant facilities.
3. We have excess capacity for quick boosts.

Efficiency:

1. Our labour productivity is high.
2. Assets are effectively utilized.
3. We produce high-quality, low-waste products.
4. We have preventative maintenance programs.
5. Our equipment is reliable.

Visibility:

1. Our systems track operations accurately.
2. We have real-time data on assets.
3. We exchange information regularly.

4. We gather business intelligence effectively.

Adaptability:

1. We reallocate orders and jobs quickly.
2. We use simulations for better processes.
3. We seize market changes advantageously.
4. We innovate to improve operations.
5. We reduce lead times continually.
6. We employ continuous improvement.

Anticipation:

1. We use demand forecasting.
2. We identify and prioritize risks.
3. We monitor operational deviations.
4. We recognize early warning signals.
5. We have contingency plans and drills.
6. We capitalize on new opportunities.

Recovery:

1. We quickly organize response teams.
2. We communicate effectively in crises.
3. We handle crises successfully.
4. We act immediately to mitigate disruptions.

Dispersion:

1. Inputs from a decentralized supplier network.
2. Production at various locations.
3. Leaders based in different locations.
4. On-site experts make key decisions.
5. Products sold in various regions.

Collaboration:

1. We use collaborative demand forecasting.

2. Data flows transparently in the SC.
3. Customers delay orders if needed.
4. We manage product life cycles proactively.
5. We invest in supplier facilities and share risks.

Organisation:

1. We encourage creative problem-solving.
2. We enforce individual accountability.
3. We train employees in diverse skills.
4. We fill leadership voids quickly.
5. We are a learning organization.
6. We care for employees.

Market Position:

1. Our brands are well-recognized.
2. Our customers are loyal.
3. Our products have a significant market share.
4. Customers differentiate our products.
5. We have strong customer relationships.
6. We communicate effectively with customers.

Security:

1. We use layered defenses.
2. We restrict access stringently.
3. We run security awareness programs.
4. We collaborate with government on security.
5. Our information systems are secure.
6. We use various personnel security measures.

Financial Strength:

1. We have significant financial reserves.
2. Our business portfolio is diverse.
3. We have substantial insurance coverage.

4. We sell products at high margins.