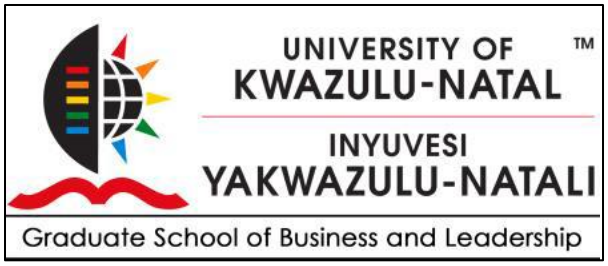

University of KwaZulu-Natal

Developing a Competitive Intelligence Strategy Model for South African Life Assurance Industry

by

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218078329

A thesis submitted in fulfilment of the requirements for the degree

of

Doctor of Business Administration

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Supervisor: Prof. Bibi Zaheenah Chummun

Date: February 2022

DECLARATION

I Mpho Lawrence Maluleka declare that

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ABSTRACT

Competitive Intelligence Embeddedness (CIE) and organisational performance studies have used various techniques and methods to explain the relationships between variables. To address this limitation in the body of knowledge, the objective of this study was to apply PLS-SEM and build a model that explained and identified the critical factors affecting CIE in the SA life insurance environment. This study was deductive and based on a non-experimental research design. Quantitative research methods and descriptive design with the positivist research paradigm were employed. The researcher developed a cross-sectional quantitative approach using smart-PLS version 3.2.7. Data were collected from 276 respondents, and the response rate was 72%. Partial Least Squares Structural Equation Modelling (PLS-SEM) was applied to estimate the proposed theoretical model. This model was examined from an explanatory-predictive perspective and exhibited a high out-of-sample predictive power. Furthermore, this study's measurement model was confirmed to be valid and reliable and acceptable. The findings of this study revealed that the R^2 value of the model was scored at 0.615, 0.506, and 0.735, which meant that the fourteen exogenous latent constructs collectively explained 61.5%, 50.60%, and 73.50% of the variance CIE, CS, and OP respectively. The model's Goodness-of-Fit measured by SRMR and RMS_theta was 0.55 and 0.101 within the acceptable benchmark. The hypothesis validated that CIE was supported by employees, strategy, information usefulness, and information providers. Also, CIE, employee role clarity, and customer satisfaction aided organisational performance. This study showed that CIE is vital in SA life assurance companies because of its close association with customer satisfaction and organisational performance. Moreover, this study highlighted that the success of CIE in SA life assurance companies is influenced by the leadership style, technological readiness of the organisation, corporate culture and the accuracy, and use of information for strategic decision-making. Future research should consider a similar study in other African countries and globally to find similarities in embedding CI in organisations. The future investigation should also consider short-term insurance and other industries to test this study's conceptual model.

Keywords: Competitive Intelligence, competitive intelligence embeddedness, customer satisfaction, leadership, strategy, sustainable competitive advantage

LIST OF ACRONYMS

AMOS	Analysis of Moment Structures
BCa	Bias-Corrected Percentile Bootstrap Confidence Intervals
BI	Business Intelligence
BSC	Balanced Score Card
CB-SEM	Covariance Base Analysis Structural Equation Modelling
CEO	Chief Executive Officer
CI	Competitive Intelligence
CIE	Competitive Intelligence Embeddedness
CS	Customer Satisfaction
ELM	Elaboration Likelihood Model
ERC	Employee Role Clarity
eWOM	Electronic Word of Mouth
GDP	Gross Domestic Products
GOF	Goodness of Fit
GWP	Gross Written Premiums
IAM	Information Adoption Model
IBM	International Business Machines Corporation
IT	Information Technology
ICT	Information and Communication Technologies

IACM	Information Acceptance Model
KM	Knowledge Management
KPMG	Klynveld, Peat, Marwick, Goerdeler
MAE	Mean Absolute Error
NFI	Normed Fit Index
OP	Organisational Performance
PwC	PricewaterhouseCoopers
OECD	Organisation for Economic Co-operation and Development
SCA	Sustainable Competitive Advantage
SPSS	Statistical Package for Social Sciences
PLS-SEM	Partial Least Squares-Structural Equation Modelling
RMSE	Root Mean Squared Error
RMS_theta	Root Mean Squared Residual Covariance Matrix
SEM	Structural Equation Modelling
SRMR	Standardized Root Mean Square Residual
VIF	Variance Inflation Factor
TAM	Technology Adoption Model
TRA	Theory of Reasoned Action
TOE	Technology Organisation Environment Framework
SA	South Africa / South African
SA's	South Africa's

SARB	South African Reserve Bank
SCIP	Society of Competitive Intelligence Professionals
US	United States of America
WHO	World Health Organisation

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Chapter One: Introduction

1.1 Introduction

With globalisation resulting in market volatility and fierce competition, leaders are compelled to understand the systematic factors that require organisations to anticipate changes in the market to respond to the macro-environment effectively (Rimita, 2019).

Consequently, organisations not adapting to the ever-changing business complexity will not survive in the new economy (Tahmasebifard & Wright, 2018). The advent of big data in financial services presents various advantages, such as digitising financial products and services; thus increasing the interactions between customers and organisations (Hussain & Prieto, 2016). This view connotes that organisations paying more attention to customer analytics and other external insights will gain competitive intelligence, create core value, and thrive in the modern and highly competitive business world.

With data pouring from almost anywhere, any time, and from any device; organisations have been facing an overload of information resulting from the rapid evolution of events and patterns, thus increasing the intensity of change in consumer behaviour, together with disruptive innovation and shortened product life cycles (Bartes, 2014a). Even so, insurers have large quantities of data since they are not fully prepared to accommodate traditional and non-traditional sources of information since they do not have the right analytical tools to make data meaningful (IBM, 2015).

This view concurs with Deloitte (2018), whose study found that 90% of insurance companies faced multiple challenges that prevented them from reaching the potential of data analytics solutions. They struggled to understand a positive business case on big data analytics capabilities.

Since the insurance industry is overwhelmed by data from various sources and providers, it is necessary for Competitive Intelligence (CI) to be used by the South African (SA) life assurance industry to collect and combine the correct available data to strategically apply it to risk management, customer experience, and improved turnaround times (KPMG, 2020).

Therefore, CI serves as a strategic tool permitting organisations to accumulate information systematically. In addition, Shujahat, Hussain, Javed, Malik, Thurasamy and Ali (2017, p. 57), describe CI as “an ethical and systematic process, program and function of gathering, analysing and managing information about the external environment for informed decision-making and ultimately competitive advantage”.

In Markovich, Efrat, Raban and Souchon (2019, p.708), CI could be “a process that produces and disseminates actionable information from and about the firm’s external and competitive and competitive environments to help managers in decision making and to achieve a competitive advantage”. CI is, therefore, a process that helps organisations make market-related decisions based on actionable information about an organisation and its external environment (De Almeida, Lesca & Canton, 2016; Kahaner, 1997).

CI is a discipline that collects and analyses information about the market and the competition for organisations to achieve competitive advantage (Tomek & Vávrová, 2008). In addition, the quality of information is improved through CI for arriving at effective decisions for the organisation to maintain its competitive position (Campos et al., 2014).

This view implies that making better decisions—based on a proper understanding of the competitive landscape—is at the heart of CI (Calof, 2016). Meanwhile, employees and management in an organisation may incorporate CI into their daily work and decision-making routines to ensure that actionable or useful knowledge flows throughout the organisation; and to enhance the development of the organisation’s competitive advantage capability; this is known as CI embeddedness (Markovich et al., 2019).

Notably, CI embeddedness augments the organisation’s know-how, productivity, competitive advantage, customer satisfaction, and performance (Amidon, Formica, Mercier-Laurent, 2005). Therefore, CI provides myriad benefits for organisations apart from its information-gathering process.

However, most organisations and researchers have focused on CI as a technique for gathering and analysing information rather than its influence on organisational performance (Markovich et al., 2019; Shujahat et al., 2017).

Consequently, studies with models that understand the drivers and outcomes of CI-related capability termed CIE are lacking (Markovich et al., 2019). Viewing CI's sights with this context in mind could be beneficial activities within the domains of the South African life assurance industry. Therefore, the main thrust of this study remains to consider entrenching competitive intelligence embeddedness in South African life assurance companies to attain superior performance

1.2 Background

With the world recently experiencing a pandemic known as COVID-19, the adversity of the pandemic continues to disrupt businesses, economies, human health, lifestyles, and society at large (KPMG, 2020). The COVID-19 pandemic and its economic crisis have worsened SA's macroeconomic conditions, resulting in a contraction of 7.2 percent in the Gross Domestic Products (Bagus, Hall, Jeenah & Sari, 2020).

The country's unemployment rate has also increased acutely. The fourth quarter of 2020 is expected to have a growth rate of 32.5 percent, compared to 30.8 percent in the third quarter, as reported by Statistics South Africa (Stats SA). Similarly, the South African Reserve Bank's Treasury predicted that this rate could exceed 50 percent by 2020, leaving more than seven million unemployed (KPMG, 2020). Stats SA has also consistently confirmed the number of unemployed at 7.2 million people in the fourth quarter of 2020, compared to 6.5 million in the previous three months.

Despite the glaring challenges imposed by the COVID-19 pandemic, SA was already dealing with an ongoing economic recession and downgraded to BB+, referred to as junk status or non-investment grade speculative, due to policy uncertainties and the lack of structural reforms (KPMG, 2020).

Prior research studies by Ćurak, Lončar and Poposki (2009), and Han, Li, Moshirian and Tian (2010) have recorded a correlation between economic growth and the insurance sector. Nevertheless, SA's current recession is expected to have a more profound and longer impact on the country's insurance sector due to early cancellations of insurance

policies by the cash-strapped customers and the pandemic and its effects (Bagus et al., 2020).

Some SA insurers have taken a significant step to reduce premiums, aligning premiums payable to the use of the insured item and providing cashback in premiums and flexible grace periods for paying premiums in quest of reducing lapses (KPMG, 2020).

Equally important, changing customer needs and behaviours disrupt traditional business models, which creates an opportunity for SA insurers to innovate and enhance their current product offerings (Bagus et al., 2020). In this manner, SA insurers should invest in end-to-end digitisation founded on a customer-focused experience design and the capability to obtain real-time information as and when events occur (Bagus et al., 2020).

In that way, SA insurers could acquire information through increased digital adoption from customers and intermediaries. While the benefits of data are cutting across all insurance business areas, insurance companies are not taking advantage of harnessing data through advanced analytics (Bagus et al., 2020).

Data and analytics offer substantial opportunities for insurance companies to generate customer insights, build closer relationships with customers, use insights to predict outcomes, and gain an advantage by creating new business models (IBM, 2015).

Inevitably, insurance companies need to constantly reposition their integrated customer value propositions, exploit CI as a competitive advantage, and adjust to changes in customer behaviour to survive in a market dominated by fierce competition (Amiri et al., 2017).

Essentially, leaders should predict factors that influence the external environment. In so doing, leaders need to define organisational goals and provide agility for organisations to develop and maintain adequate information and knowledge management processes such as CI to achieve their strategic objectives and maintain competitive advantage, rather than merely concentrating on saturated data (Bartes, 2014c). In this way, transforming competitor information into CI contributes to sustainable competitive advantage and is key to organisational performance.

Since the insurance industry relies on accurate and reliable information, recent advancements in Information and Communication Technologies (ICTs) and the internet have brought disruptive forces to the fore, demanding more information use than historical analysis to compete effectively (Andersen & Wong, 2013, p. 3).

So radical change in this environment requires organisations to respond quickly with increased strategic agility, flexibility, and innovation to manage the wealth of information as it manifests to create and sustain competitive advantage (Sajdak, 2015). CI is gathered to avoid and detect futuristic risks and opportunities and improve strategic and technical decision-making processes (Ansoff, 1980; Porter, 1980, p.74).

Essentially, CI aids the strategic planning process, and it collects relevant information from the competitive environment to ensure the sustainability of organisations in both the short and long-term (Badr, Wright & Pickton, 2004; Choo, 2002; Pellissier & Kruger, 2011).

However, companies in developing countries, including SA companies, only use CI for new and pending legislative trends liable to impact them rather than using it for keeping abreast with domestic and international trends that affect their ability to compete and survive (Pellissier & Kruger, 2011; Sewdass & Du Toit, 2014; Du Toit, 2015).

This study seeks to cultivate a strategic model for the SA life assurance industry. The researcher believes this study can provide new insights and knowledge beneficial to the SA insurance industry, including other organisations and top management, to sustain organisational performance in the new digital economy.

The research question forming the primary focus of this study is: Does competitive intelligence—through customer satisfaction—influence organisational performance in the South African life assurance industry?

1.3 Rationale of the Study

The past ten years have witnessed some substantial increment in organisations that experience susceptibility to respond to the winds of change in the political environment, economic, technological, and regulatory (Sepahvand, Nazarpoori & Veisi, 2016; Vidigal, 2013). Consequently, the evolution of innovative organisations established on knowledge and networks has emerged to keep up and respond to the complexity and ambiguity of the ever-changing business environments (Ahmad, 2015).

Insurance is not isolated from the challenges of reacting more intelligently to the pace of change. Currently, the insurance sector is confronted with complex, vague, and changing business environments characterised by unclear organisational boundaries, which has glimmered the growing need for CI practices to maintain their position and survive in a dynamic business environment (Muritala & Ajetunmobi, 2019). Inevitably, most organisations have accepted the use of CI to build and maintain their competitive edge in today's unpredictable economy (Muritala & Ajetunmobi, 2019).

Equally, insurance companies changed their attitude to embrace market research and CI in their operations to attain competitive advantage (Johns & Van Doren, 2010). CI characterises, acquires, analyses, and transmits intelligent information about products, consumers, and rivals (Mabe, Sibeko, Morake & Nkadimeng, 2019). Regulations, customers, and suppliers are all included in CI (Du Toit & Strauss, 2010, p.22).

Previous studies by Du Toit (2015), Pellissier and Kruger (2011), and Sewdass and Du Toit (2014), however, found that companies in developing countries, including South African companies, only employ CI for new and pending legislative trends rather than keeping up with local and global trends in the market liable to influence them.

In contrast, a recent study by Muritala and Ajetunmobi (2019) showed that CI positively correlated with a competitive advantage of selected insurance firms in Nigeria. Pellissier and Kruger's (2011) study in the SA long-term insurance industry showed that CI was more established in prominent companies. Its primary use was for strategic decisions and gaining insights about customer analytics and markets.

This study highlights the significant gaps in peer-reviewed articles on CI relating to the SA insurance industry, as most CI articles are written by authors from other countries (Amiri et al., 2017; Hamidizadeh et al., 2014; Sepahvand et al., 2016).

Notably, most academic articles relating to CI are published by authors as afield as North America and Europe, thus suggesting few from South Africa as proclaimed by Du Toit (2015, p. 18). Concurring, Maune's (2014c) findings showed that CI was still in its early stages twenty years after it was introduced in South Africa, suggesting limited information on CI activities in SA (Du Toit, 2015; Sewdass & Du Toit, 2014).

With business practices changing the dynamics of competition among organisations, the integration of information and ICT and digitisation enhances the competitiveness of companies in the digital economy (Anderson & Wong, 2013). SA insurance companies, therefore, need to anticipate uncertainties and monitor competitor actions by obtaining internal and external information.

Therefore, the SA life insurance companies need to embed a CI capability in their operation that enables knowledge creation and transfer acquired from markets and the organisations' stakeholders (Chevallier, Laarraf, Lacam, Miloudi & Salvetat, 2016).

Taking into consideration of the contextual gaps and limited empirical review along with the observations made by Markovich et al. (2019), it has been observed that the studies with models that understand the drivers and outcomes of CI-related capability were lacking.

This research develops a conceptual model that integrates the micro and macro-environments with information attributes, drawing attention to CIE's best practices; thus, leading to organisational performance. This study can fill a gap in academic knowledge and the ability to address issues outside academia for organisations to improve and maintain a sustainable competitive advantage during turbulent times.

1.4 Problem Statement

During the COVID-19 pandemic, SA insurance companies faced challenges due to the lack of effective CI practices and processes, resulting in a dramatic rise in mortality and a decline in customers. The Covid-19 epidemic has motivated SA insurers to harness and unleash big data technology to increase customer value. With CI and digital transformation, they can discover new revenue prospects and leverage big data to increase customer value.

In SA, studies relating to CI in insurance are generally limited. For example, Pellissier and Kruger (2011) investigated the use of Strategic Intelligence systems in the SA long-term insurance industry. It was discovered that longer-term insurance companies conducted more CI operations than smaller companies.

Most studies on CI and insurance were undertaken in foreign countries (Amiri, Shirkavand, Chalak & Rezaeei, 2017; Hamidzadeh, Roosta, Lajevardi & Mohamadian, 2016; Muritala & Ajetunmobi, 2019; Muritala, Asikhia, Makinde &Akinlabi, 2019; Sepahvand et al., 2016). This indicates a research gap, and further CI research for the SA life insurance market is required.

Markovich et al. (2019, p.708) opined that the organisational capability developed from embedding CI into decision-making and provision of products and services is “an organisationally-embedded non-transferable firm-specific resource whose purpose is to improve the productivity of the other resources possessed by the firm”. Investing in CIE helps organisations, their employees, customers, and even business partners by increasing customer satisfaction, revenues, and market share.

While embedding CI has multiple benefits and results, the outcomes are generally not fused in most research models. An instance is the CI process model by Amiri et al. (2017), Pellissier and Nenzhelele (2013), Gilad’s (2016) information conversion model, Dishman and Calof’s (2008) model of CI, McGonagle and Vella’s (2008) CI cycle, Maritz and Du Toit’s (2018) CI strategy relationship model, and Du Plessis and Gulwa’s (2016) CI strategy framework. In concurrence with Markovich et al. (2019), these models focus on

describing processes followed to develop a CI system instead of exploiting the drivers and outcomes of CI.

Moreover, these models suggest that CI systems are developed to gather information from internal and external sources, such as the organisation's value chain, competitors, customers, suppliers, and other stakeholders (Gilad, 2016). These factors are captured by Tornatzky and Fleischer's (1990) Technology-Organisation-Environment (TOE) framework.

The TOE explains elements in three forms about an organisation's context that impact its adoption decisions (Piaralal, Nair, Yahya & Karim, 2015). The TOE modelled by Duh and Fabiao (2018) for a financial institution proposes internal factors such as top management support, financial resources, and employee capability, while customer pressure, information technology vendor support and competitive pressure are external factors.

Concerning adopting innovative and competitive ideas, Erkan and Evan's (2016) Information Acceptance Model (IACM) suggests that information attributes predict the adoption of information. Furthermore, IACM expands the notion of information adoption to include consumer behaviour to explain the process that influences behavioural intentions.

In the context of CI, the CIE model by Markovich et al. (2019) suggests that information attributes such as perceived quality of information sources and information accuracy are essential drivers of CIE. Furthermore, CIE capability understands the drivers and performance outcomes of the organisation. However, most studies in CI models have not exploited its drivers and outcomes except for Nasri's (2012) CI strategic benefits model.

This model by Nasri (2012) advocates that the CI outcomes are innovation, marketing differentiation, low cost, customer satisfaction, new market anticipation, revenue prospects and market share. Consistent with other CI models, this study also focused on highlighting processes and not providing clear, measurable drivers and outcomes. In contrast, the CIE model by Markovich et al. (2019) comprised CI's benefits, drivers, and outcomes.

In this research model, Markovich et al. (2019) suggest that CIE's outcomes are firm performance. Developing a CIE capability advances the implementation of the CI cycle through the organisation. Although some aspects of CIE have been explored in current models, no research has investigated the link between drivers of different models.

Therefore, there is a need for a comprehensive model for deployment and effective execution of CI within SA life insurance companies. CIE practices are examined in depth within the present research context, and a model for organisations to flourish in the competitive environment is provided.

The model can be used to assess CIE, identify the strengths and weaknesses of organisations, and improve CI practices. This study develops an integrated model that addresses the gaps in the literature review and earlier models and displays the CIE drivers and their interactions, which enhances organisational performance.

This study adds to the CIE literature by connecting it to numerous characteristics and investigating its association with overall performance, something few studies have done before. Furthermore, this study will fill a gap in academic knowledge and address issues outside academia for organisations to adopt this study's research model to attain superior performance.

1.5 Research Objectives

Given the research problem discussed above, this study's primary and secondary research objectives are formulated. This study integrated relevant aspects of the TOE modelled by Duh and Fabiao (2018), the IACM by Erkan and Evans (2016), and the CIE model by Markovich et al. (2019). This mixed model aims to examine the drivers of CI in the SA life assurance companies that lead to CIE outcomes.

This research's primary objective is to investigate the effect of CIE on organisational performance in SA life assurance companies. From the developed integrated conceptual model, the following secondary objectives of this study are to be achieved.

1. To examine how employee role clarity, information attributes, and organisational factors impact CIE and performance in SA life assurance companies.

2. To examine the extent to which market factors influence CIE and performance in SA life insurance companies.

3. To examine the influence of CIE on customer satisfaction and the performance of SA life insurance companies.

1.6 Research Hypothesis

This study is experimental quantitative research. There is considerable and significant knowledge available on CI; consequently, the researcher did not employ quantitative questions for this study. The research has instead incorporated related components of the CIE by Markovich et al. (2019), IACM by Erkan and Evans (2016) and the TOE framework by Duh and Fabiao (2018) to develop an integrated conceptual model in Figure 1 in which seventeen hypotheses were produced as outlined below:

- H1: Strategy contributes positively to competitive intelligence embeddedness.

- H2: Leadership commitment and support has a positive influence on competitive intelligence embeddedness.

- H3: Structure and process have a positive influence on competitive intelligence embeddedness.

- H4: Employee capability leads to competitive intelligence embeddedness.

- H5: Quality of competitive information has a positive impact on competitive intelligence embeddedness.

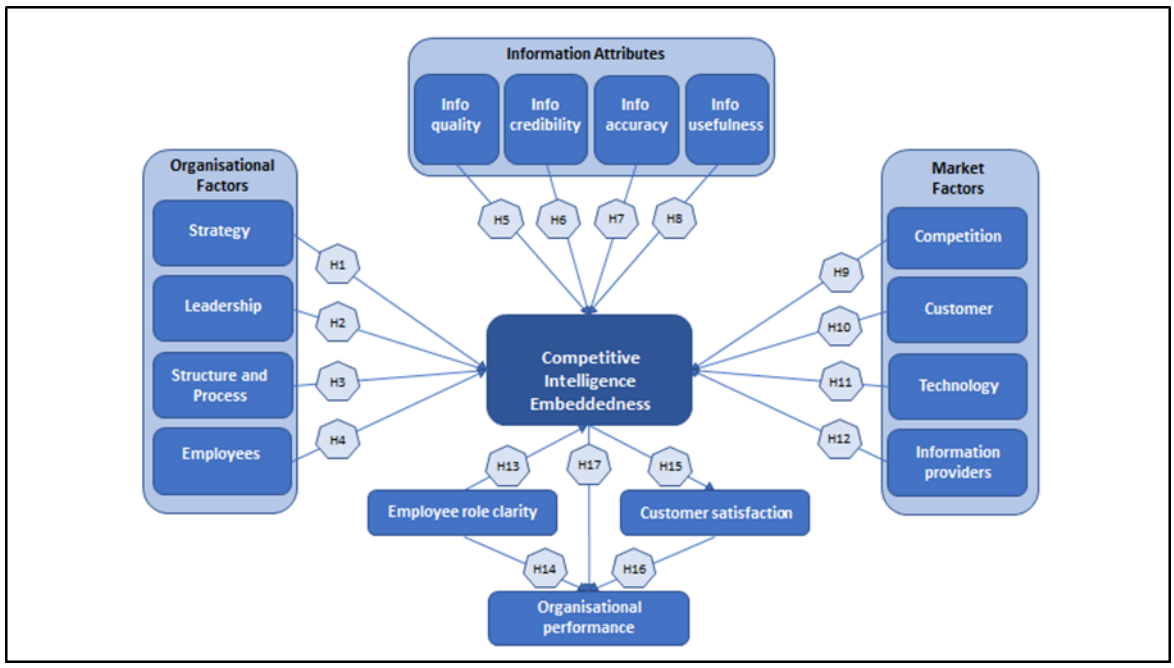
- H6: Credibility of competitive information has a positive impact on competitive intelligence embeddedness.

- H7: Accuracy of competitive information has a positive impact on competitive intelligence embeddedness.

- H8: Usefulness of competitive information has a positive impact on competitive intelligence embeddedness.
- H9: Competitor information is positively influenced by competitive intelligence embeddedness.
- H10: Customer insights is positively influenced by competitive intelligence embeddedness.
- H11: Technology readiness is positively influenced by competitive intelligence embeddedness.
- H12: The organisation's enduring relationship with information providers is positively related to competitive intelligence embeddedness.
- H13: Employee role clarity positively influences organisational performance.
- H14: Employee role clarity positively influences competitive intelligence embeddedness.
- H15: Competitive intelligence embeddedness positively influences customer satisfaction.
- H16: Customer satisfaction positively influences organisational performance.
- H17: Competitive intelligence embeddedness positively influences organisational performance.

The conceptual model in Figure 1.1 below covers this study's independent, dependent, mediating, and moderating variables, including the hypothetical relationships among various constructs.

Figure 1.1: This Study's Conceptual Model and Hypothetical Relationships



Source: Author's own model

1.7 Research Methodology

This study is deductive with a non-experimental research design; therefore, quantitative research methods and descriptive design with the positivist research paradigm were employed because they support quantitative methodology (Antwi & Hamza, 2015).

An online survey was employed to collect information from the participants recruited for the study. This study is quantitative, and it generally relies on random or representative sampling to generalise the findings from the sample to the population (Rudestam & Newton, 2014).

The total population of the SA life assurance industry was 130000 during the time of this research, and a probability sampling method was used to select participants for this project. A simple random sampling was employed to ensure that each participant had an equal opportunity to participate in the study (Rahi, 2017).

The researcher employed Raosoft's calculator and performed statistical calculations to achieve the sample size of 384 participants to conduct the research successfully. As a cross-sectional study, variables were examined, and data was collected at a specific point in time (Zikmund et al.,2013).

A self-administered questionnaire was emailed to participants of the SA life assurance industry through random selection. All the respondents were required to respond to closed-ended questions on a 5-point Likert-type scale rating (Saunders, Lewis, Thornhill, 2016).

According to Hair, Babin, Money, and Samouel (2003), Structural Equation Modelling (SEM) is more appropriate for sample sizes of 200 and more. SEM was employed because the researcher established links between constructs and the hypotheses (Ringle, Sarstedt, Mitchell & Gudergan, 2020). This research also divided quantitative data analysis into preliminary data analysis and hypothesis testing.

Statistical Package for Social Sciences (SPSS) 24.0 and Partial Least Squares-Structural Equation Modelling were used to analyse the data for this study (PLS-SEM). Descriptive statistics were used to identify common themes that emanated from responses supplied to the questionnaires. PLS-SEM was used to analyse quantitative data forms downloaded from Google Drive to investigate the potential associations between variables.

1.8 Structure of the Thesis

The following section describes each chapter of this thesis.

1.8.1 Chapter One – Introduction

This chapter describes the study by first outlining the problem and the research objective and hypothesis. Furthermore, the research methodology, the conceptual model, and the study's significance and contributions are provided.

1.8.2 Chapter Two–Contextual and Systematic Factors Impacting the Insurance Industry

This chapter provides an overview of the worldwide insurance sector, the African and South African insurance industries and the connection between insurance and fiscal development. The influence of competitive intelligence in organisations and emerging markets is discussed at the end of this chapter.

1.8.3 Chapter Three – Theories and Models Explaining the Application of Competitive Intelligence

This chapter presents various theoretical approaches and models relating to the research problem of this study. The chapter critically reviews the existing body of knowledge relevant to this study.

1.8.4 Chapter Four – Conceptual Model and Hypothesis Development

This chapter provides the theoretical background underpinning the proposed conceptual model. This chapter concentrates on theories and modified models such as the TOE by Duh and Fabiao (2018), IACM by Erkan and Evans (2016), and the CIE model by Markovich et al. (2019).

1.8.5 Chapter Five – Research Methodology

This chapter discusses the research methods used to experimentally test the conceptual model and meet the study's goals, as stated in the first chapter. The chapter also discusses the target population, sampling procedure, and data collecting and analysis, including the study's ethical considerations.

1.8.6 Chapter Six – Analysis and Presentation of Results

The survey's empirical findings are presented in this chapter. The descriptive statistics, normality testing, and the Smart Partial Least Square based on structural equation modelling are the key statistical data analysis employed in this chapter.

1.8.7 Chapter Seven – Discussions

This chapter addresses the findings reported in Chapter Six, the primary concerns uncovered in the analysis, and interprets and links the findings to data from prior but similar investigations.

1.8.8 Chapter Eight – Conclusions and Recommendations

The final chapter discusses insights gained from empirical research findings. A summary of the study's key results is presented, and conclusions are drawn based on the study's findings. The study's practical and theoretical contributions are then outlined. This chapter also discusses the study's weaknesses and suggestions for further research.

1.9 Conclusion

The main reason for conducting this study is to determine what key attributes are essential to ensure that competitive intelligence embeddedness leads to organisational performance. The resulting analysis provides insights into how the SA life assurance industry can embed competitive intelligence practices in its operation to manage big data proactively and respond quickly to emerging trends.

Furthermore, this study developed a conceptual model, a planning tool that organisations can use to gather intelligent information about customers and markets insights, and the recommendations from this study have the potential to assist the SA life assurance industry and other industry sectors in developing and maintaining effective knowledge management processes in realising strategic goals that foster sustainable competitive advantage in the new digital economy.

Moreover, this model may aid decision-making, alert organisations of prevalent changes in the competitive environment, and implement plausible strategic options to claim and maintain a distinct position and survive in a fiercely contested market.

This chapter introduced the study, and it discussed the general overview and scope of the study. The study background, research challenges, and the development and methodology of the research objectives were all explained in detail.

Also, this chapter presented the proposed integrated conceptual model developed in this study. The chapter also provided an overview of theoretical and practical contributions and the thesis structure.

The next chapter discusses contextual and systematic factors impacting the global insurance industry, including South Africa.

Chapter Two: Contextual and Systematic Factors Impacting the Insurance Industry

2.1 Introduction

Some issues, such as the ongoing trade wars between China and the United States of America (USA) and the prolonged Brexit negotiations, have impacted the global economy in one way or the other. Such geopolitical and business environments have adversely affected the macroeconomic stability of developed and developing countries' economies.

As these events unfold, organisations should use CI in their strategic planning processes to better understand the cultural, economic, legal, and political climate in the global context (Nunes & de Souza Lequain, 2016). The financial services business in Africa has grown dramatically over the previous decade, thanks to mobile money developments and increased financial inclusion and profitability (Adeleye, Debrah & Nachum, 2019).

In contrast, the global insurance industry is experiencing turbulent times attributed to the persistence of low-interest rates, challenging equity markets and tighter regulatory regimes (Binder & Mußhoff, 2018, p.4). Despite these glaring challenges, the global industry grew by more than 4 percent in 2017, which is on par with its compound annual growth rate from 2010 to 2016, attaining €4.6 trillion in total premiums (Binder & Mußhoff, 2018, p.7).

According to Binder and Mußhoff (2018, p.4), Africa, Asia-Pacific, and Latin America are the fastest growing regions globally in the life insurance industry. The aggregate growth of insurance in the developing and developed countries' financial sectors has shifted attention to the insurance growth nexus (Olayungbo & Akinlo, 2016).

Meanwhile, Africa's insurance industry is mainly underdeveloped by global standards' persistent lower insurance infiltration (Muguto, 2018). The African insurance industry has yet been beset by continuous disruptions since the 2008 global financial crisis, resulting in slow growth prospects.

However, the African insurance industry has adapted well to the regulatory disruptions over the past ten years (Muguto, 2018). Lately, technological developments, along with the pace of the new digital economy, among others, are some of the tectonic shifts forcing insurers globally to adjust their business models (Binder & Mußhoff, 2018, p. 4).

For this reason, insurers are looking to invest afield in emerging markets to scale their businesses, with growth expected to come from Asia and Africa (Freiling, Behrens, Sachdev & Nadkarni, 2017, p.3). Therefore, a growing middle-class in some countries is a favourable ideal market for insurers to pursue growth in 2020 (Ernest & Young, 2019, p.6).

This chapter reviews different segments impacting this study. The literature reviewed highlights the role of the insurance industry in the global economy, including Africa, and South Africa, among the significance of insurance and the connection between economic growth and insurance. Lastly, the importance of competitive intelligence in organisations and emerging markets are explored.

2.1.2 The Global Insurance Industry

Global insurance depends on various economic and non-economic factors impacting predictions for its future performance. Several challenges cloud the horizon of the global life insurance industry, and purposely, this empirical review mainly focuses on the global insurance markets in the United States, Europe, and Asia-Pacific.

The global insurance sector has been disturbed in the last five years by the rapid pace of technology development, shifting client expectations, ongoing regulatory reform, and the fear of new market entrants (PwC, 2019, p.3). Furthermore, PwC (2019, p.3) reiterates that the disruptions have brought significant change that allows insurers to add more value and offer a more focused customer-centric experience.

Additionally, disruptions have positioned industry sectors to places where young and sophisticated customers access online and social media information to interact with future customers.

As cited in Oitsile, Galebotswe and Sekwati (2018, p.843), Ernest and Young (2014) indicated the significant growth of the global insurance industry, a contribution of 6.5 percent of the global GDP. Furthermore, Oitsile et al. (2018, p.843) stress that while developed countries account for a larger share, developing countries reported rapid growth for the same period.

China and other emerging markets in Asia are to drive global demand for insurance for many years to come (Swiss Re Sigma, 2018, p.1). Furthermore, Swiss Re Sigma (2018, p.1) maintains that even with 2008, the growth gap narrowed between advanced and emerging marketers, and the growth in insurance activities is expected to shift from the west to the east. Early in the year, the global insurance industry remained resilient, continued to generate growth, and maintained overall profitability despite the turbulence in the global economy (Friedman, Canaan, Gokhale & Ashani, 2019, p.3).

Global insurance premiums are projected to grow by roughly 3 percent annually in real terms over the next two years, along with an increase of 1 percent from 2018 in life insurance premiums, driven mainly through emerging markets, with China being the main contributor (Swiss Re Sigma, 2018, p.1). This points towards insurance market development being a strong predictor of growth (Chamberlain, Camargo & Coetze, 2017).

Given that the global economy is poised for growth, the current low-interest rates environment, stagnant growth, and the growing likelihood of a worldwide depression pose a challenging economic reality for insurers worldwide (Ernest & Young, 2019, p.5). Indeed, the global insurance industry is struggling to grow and maintain profitability, citing maturing markets and the current unpredictable economic environment conditions (Friedman et al., 2019).

Essentially, mature markets in the US and Western Europe have exhibited slower growth rates than insurance in emerging markets (Binder & Mußhoff, 2018, p.4). Hence, insurers in the US posted a decline in the underwritten gain of $ 5.4 billion compared to $6.1 billion for the same reporting period in 2018 (Friedman et al., 2019, p. 3). These highlights signify that the US insurance industry is experiencing low growth tweaked to the deterioration of

insurance penetration of 3.9 and 2.9 percentile points between the 2008 and 2019 reporting period (Friedman et al., 2019, pp.3-4).

In contrast, European insurers grew 0.01 percentile points. They earned $ 686 billion in Gross Written Premiums (GWP) between 2013 and 2018, while insurance penetration as a percentage of GDP remained at 2.8 percentile points for the same period (Manchester, Santenac & Russignan, 2019, p.11). Similarly, European insurers face more challenges than their industry peers in other global regions.

The industries' growth prospects face different expectations and opportunities (Manchester et al., 2019, p.27). Furthermore, Manchester et al. (2019, p.7) point out that low-interest rates and weaker economic growth add to the persistent challenges faced by life insurers in stimulating growth. Consequently, the outlook of the European insurance industry remains bleak as negative growth rates in major markets have been negligible. Economic growth across Europe has been mostly anaemic. *Albeit*, Germany, one of the European countries' stronger economies, is now struggling, and European insurers are pursuing expansion opportunities in emerging markets in Eastern Europe and Asia, respectively (Manchester et al., 2019, p.4).

On the brighter side, many developing markets, especially in Asia, are experiencing more substantial growth and a growing middle-class, as reported by Ernest and Young (2019, p.6). Notably, China and India contributed immensely to the Asia-Pacific region's life insurance growth in 2016 (Binder & Mußhoff, 2018, p.16). Equally, the emerging market's wealth is significant, with GDP rising by 1 percent in 2018, impacting premium volumes more significantly than a decade ago (Swiss Re Sigma, 2018, p.1).

Furthermore, Swiss Re Sigma (2018, p.1) added that many emerging markets have advanced to a sharper spot of the insurance ″S-curve″. Consequently, the impact of income growth is more significant on insurance demand. Then, insurers seeking expansion in diverse markets should consider the Asia-Pacific region due to its rapidly expanding middle-class population across multiple countries (Peters, Santenac & Russignan, 2019, p.4).

This view indicates that the Asia-Pacific insurance industry still maintains China's driven growth, and positive performance from South Korea is consequential to an upsurge in premiums and insurance penetration (Peters et al., 2019, p.6). Nevertheless, due to low-interest rates and declining treasury bond yields, the Asia-Pacific area confronts identical macroeconomic issues and distinct vulnerabilities as the rest of the globe.

Binder and Mußhoff (2018, p.14) reported a 12 percent increase in the Asia-Pacific region during the reporting period between 2015 and 2016, implying a 7 to 9 percent increase by 2020. So, the major emerging markets; China and India, are expected to grow by 15 percent over the coming year. However, profitability in these markets is likely to decline as insurers compete for market share (Binder & Mußhoff, 2018).

These facts indicate that the life insurance industry in Asia-Pacific is not isolated from experiencing slowdown growth despite posting a 21 percentile points increase GWP of $1,019 billion, while insurance penetration contracted by 5 to 3.8 percentile points between 2013 and 2018 (Peters et al., 2019, p.20). Even if China has delivered the most robust growth in the global insurance market, the global economy will not sustain this achievement since it is expected to fall into a recession in 2020 (Peters et al., 2019, p.9).

With insurers globally facing low investment yields and tightening regulation and overcapacity in many markets, data and technology will become drivers and enablers for the overall industry to grow its profits in the future (Swiss Re Sigma, 2018, p.11).

Importantly, insurers' technology investments will yield efficiencies and facilitate access to new risk pools to close the existing protection gaps and improve the economic and social resilience (Swiss Re Sigma, 2018, p.27). Equally, automation and digitisation will become increasingly important to achieve efficiency gains.

Digitalised information would improve processes across the insurance value chain to serve customers and make effective underwriting and pricing decisions (Swiss Re Sigma, 2018, p.11). In addition, the upsurge of the internet and mobile technologies will contribute to adopting new insurance products (Ernest & Young, 2016a, p.35). That means more customers may be buying insurance on mobile phones resulting in Asia speeding ahead

of the rest of the world in the digital customer experience and distribution (PwC, 2019, p.3).

Near the end of 2019, the world faced a massive disaster. The COVID-19 virus spread quickly and infected millions of people worldwide at an alarming rate, prompting authorities to take drastic measures to contain it. The World Health Organisation (WHO) reported on December 18, 2020, that the total number of COVID-19 cases recorded worldwide was 72,851,747. The total number of deaths was 1,643,339; the US suffered the most, with 16,446,844 cases representing 22.58 percent of the total cases and 301,536 casualties representing 18.35 percent of the total deaths in the world, with India suffering the least.

Consequently, the pandemic triggered a major global economic crisis, exposing many businesses to risk. Furthermore, the COVID-19 outbreaks have slowed global economic activity due to mobility restrictions imposed to stop the disease from spreading, resulting in supply and demand shocks to the global economy.

As most global economies implemented full or partial lockdowns, these extreme measures halted consumption and production, weakened demand, and dampened future growth in 2020 and 2021 (Pocock, 2020). The International Monetary Fund (2020, p.2) reported that the world economy would enter a recession due to widespread disruptions caused by the COVID-19 pandemic.

Furthermore, International Monetary Fund (2020, p.2) predicted the global economy to plummet from 2.9 percentile points in 2019 to -3 percent in 2020, which is lower than growth prospects during the 2008 global financial crisis. Similarly, the Insurance Information Institute (2020, p.1) reported that the COVID-19 outbreak would likely slow global GDP growth to 2.3 percentile points, down from 3.3 percentile points the previous year, making a 2021 economic recovery unlikely.

Moreover, the Insurance Information Institute (2020) reported that the global insurance industry would be impacted by lower premium growth attributed to the decline in the global GDP and an increase in insurance claims resulting from the pandemic.

In contrast, the OECD (2020, p.1) estimated that the COVID-19 outbreak could reduce the global GDP to just 1.5 percentile points in 2020, while lockdown extreme and less extreme lockdowns are likely to remain in place for longer affecting up to one-third of GDP in major economies. As these events unfolded, insurers worldwide were affected by a sharp slowdown in economic activity, which undermined growth prospects and condensed insurable exposure (Shaw, 2020, p. 3).

While the COVID-19 crisis was still significantly impacting businesses and the global economy, the insurance industry, impacted by mortality claims, reacted quickly to the crisis. The COVID-19 pandemic has changed the global insurance industry's economic environment and digital strategic transformation. As the broader economy recovers and responds to the endemic, insurers worldwide can quickly embed digital transformation and CI to maintain sustained growth, improve enterprise competitiveness, and contribute to a country's economic recovery.

The COVID-19 pandemic is now in its third year and shows no signs of abating. The researchers at Universitat Pompeu Fabra's Centre for Research in Health Economics in Barcelona reported that the novel coronavirus was wreaking havoc in nearly 200 countries, killing over 5.3 million people due to the contagious Delta variant until the last week of December. Furthermore, their study estimated that the COVID-19 pandemic has cost over 20.5 million years of life in 81 countries, resulting in a drop in average life expectancy, posing more challenges for the global insurance industry, which withstood record claims in last year's third wave.

With the Omicron variant being the most mutated and transmissible of all COVID-19 variants, the number of deaths and hospitalisation has declined. Despite the prevalence of the COVID -19 endemic, currently, attention is focused on geopolitical conflicts and instability, which threaten economic growth by causing supply chain disruptions, volatile energy prices, and rising interest rates. Insurers globally still face several challenges. However, insurance companies can use big data analytics tools and CI to develop historical customer data, continuously improve customer experience, and develop products that meet the wishes and needs of customers.

2.1.3 The African Insurance Industry

In recent years, collapsing oil prices and other minerals have introduced vulnerabilities for Africa's economy and emerging markets. The slowdown in China's growth rate, in tandem with the rapid appreciation of the US dollar contributed to weaker economic output for Africa (Ernest & Young, 2016a).

Growth in China's economy remained at 6.8 percent in 2017, while sub-Saharan Africa achieved 2.6 percent growth over the same period, and was expected to rise to 3.4 percent in 2018 (Muguto, 2018, p.1). According to Kambou and Steinbach (2019, p. 108), sub-Saharan regions growth was appraised at 2.7 percent in 2018 due to weaknesses in economic activities in Angola, Nigeria, and South Africa.

Africa's five fastest-growing countries, Algeria, Egypt, Morocco, Nigeria, and South Africa, grew by 3 percent compared to the rest of the continent at 4 percent (African Development Bank 2020, p.1). Additionally, Kambou and Steinbach's (2019, p.108) anticipated growth in sub-Saharan regions was 3.4 percent in 2019 and 3.7 percent between 2020 and 2021. Consistently, African Development Bank (2020, p.1) 2019 also estimated a 3.4 percent growth for Africa, with expectations to increase by 3.9 and 4.1 percentage points, respectively, during 2020 and 2021.

Similarly, the Africa Insurance Organisation (2019, p.11) states that Africa's GDP grew from $ 2.19 trillion to 2.34 trillion, equating to a nominal growth rate of 6.7 percent. Furthermore, Africa Insurance Organisation (2019,p.11) mentions that Nigeria, SA, Egypt, and Algeria were the largest economies in the continent, thus accounting for more than 50 percent of Africa's GDP.

Sub-Saharan Africa is a diverse region that presents challenges, opportunities, and risks for the insurance industry (Ernest & Young, 2016b). Despite Africa's challenges and slow growth, the African insurance industry has a moment. The old ways of doing business are set aside, with new realities explored (Muguto, 2018). In 2015, Africa's life insurance premium accounted for 1.7 percent of the global market share, and its growth declined by 2.8 percent to $44 billion compared to the previous year (Swiss Re Sigma, 2016, p.34).

While the African insurance industry continued to be disrupted, insurance executives pursued innovative ways to seize nascent growth opportunities (Muguto, 2018). With the upsurge of financial services in Africa, the region's insurance sector's Growth in Written Premiums (GWP) of $ 60 billion was estimated to post decent growth in the following years (Muguto, 2018). Consistently, African insurance generated a value of $ 61.1 billion in GWP in 2019, which is expected to grow substantially between 2020 and 2025 (IMARC, 2020).

Meanwhile, the sub-Saharan insurance market will be more attractive for organic growth, mergers and acquisitions, and new product development attributed to Africa's demographic transformation, sustainable economic expansion, and potential investments (Ernest & Young, 2016b). For now, South Africa (SA) continues to be a gateway to the rest of Africa due to its mature, sophisticated, and competitive insurance industry (KPMG, 2019). In this context, SA, Nigeria, and Egypt will be considered in this review since they are relatively large insurance markets in Africa.

The African life insurance market is poised for the fastest growth amid the global life industry (Ngwenduna, Hayes & Angove, 2015). This growth was represented by 1.3 billion in Africa's population, which accounted for 16.5 percent of the world's total population early in 2019 (Africa Insurance Organisation, 2019, p.11). Therefore, significant population growth, rising per capita incomes, and low insurance penetration create growth opportunities for life and non-life products (Ernest & Young, 2016b).

Equally, rapid urbanisation, the growing middle-class, improving internet connections, and technological advancements are critical drivers for insurance growth in the African region (IMARC, 2020). The African region consists of several underdeveloped and developing economies.

Nonetheless, the continent's insurance industry is underdeveloped and contributes less to the region's economy (Ngwenduna et al., 2015). This fact signifies that Africa's insurance market is the least penetrated globally, even with myriad opportunities for growth (Muguto, 2018). The low market penetration has also led to rising consumer demand and new technologies (Ernest & Young, 2016b).

This prospect presents many untapped opportunities to drive the insurance sector's future growth (IMARC, 2020). While insurance penetration across Africa remains very low, SA remains the most dominant market, with Nigeria lagging. Again, this demonstrates the untapped market potential presented by the rest of the African market (Muguto, 2018). This calls for Africa's insurers to develop various measures and strategies to enhance insurance penetration and build their market presence (Africa Insurance Organisation, 2019).

Futuristic in the long-term may open new markets for insurers based on Africa's growing population (Ernest & Young, 2019). According to Africa Insurance Organisation (2019, p. 11), Africa's GDP grew by 1.07 percent to $ 2.34 trillion, with Nigeria, SA, Egypt, and Algeria accounting for more than 50 percent of the continent's GDP following the deep recession in 2015 and 2016 that exposed Africa's vulnerability to external shocks.

Based on the global trade tensions, the slowdown in China's economy—Africa's most important export market and the persistent threat of the COVID-19 outbreak; Africa's growth prospects in 2020 and 2021 have heightened (Africa Insurance Organisation, 2019). In 2017, total African insurance premiums amounted to $ 66.7 billion after recovery from a steep decline in the 2015 and 2016 economic crisis, thus indicating that Africa's insurance markets have stabilised after the economic recession (Africa Insurance Organisation, 2019, p.16).

This organisation asserts further that growth is yet to spring back to the pre-crisis years while low economic growth and unemployment will continue to slow down the pace of growth in Africa's insurance sector (Muguto, 2018).

However, insurers across Africa envisage insurance premiums to grow between 2017 and 2020 despite harsher macroeconomic instability (Muguto, 2018). In all probability, the African insurance industry has shown resilience during the economic downturn and continues to benefit from its underlying growth story (Africa Insurance Organisation, 2019).

Recently, African insurers sought to expand their operation in neighbouring markets to fill the gap created by some international insurance players who disinvested in response to continuously eroding margins (Africa Insurance Organisation, 2019; Ngwenduna et al., 2015).

Although the SA insurance market is mature, with the highest insurance penetration by regional peers, this points toward lesser growth projections in the future, given the country's sluggish economic growth (Muguto, 2018). Swiss Re Sigma (2016, p.32) notes a decline in single and recurring premiums as the weakening economy impacted household incomes.

Noticeably, Africa's slow growth in major oil-exporting countries and its weak economic environment, lower commodity prices, and rising inflation are vital challenges that are likely to reduce premiums growth (Swiss Re Sigma, 2018). To achieve exponential growth, insurers across Africa should adopt outward-looking strategies focusing on customer needs and changing behaviours. Consequently, this will increase penetration into Africa's underinsured market (Muguto, 2018).

The African insurance industry should incorporate behavioural science techniques to nudge customers in a beneficial direction for stimulating insurance activities (PwC, 2019, p.3). They should use digital technology to gain insights from behavioural economics and perform data analytics to understand consumer buying behaviours (Muguto, 2018; Swiss Re Sigma, 2018). Furthermore, Swiss Re Sigma (2018) stresses that digital technology reduces distribution and administration costs, thus making insurance accessible to the lower-income group.

Mobile technology and social media are also integral to doing business in Africa. Therefore, insurance companies should leverage mobile distribution technologies to access new risk pools and distribute life insurance to the majority of the population living in low-income groups (Muguto, 2018; Swiss Re Sigma, 2018). The dawn of the internet and mobile platforms will likely increase insurance coverage in SA's growing middle-class (Ernest & Young, 2016a, p.6). SA telecoms are used as distribution mechanisms to access and penetrate low-end consumers with insurance products (PwC, 2019, p.4).

Equally important, insurers have partnered with online retailers to distribute their products to increase their penetrative reach to all groups of potential customers. The impact of Insuretech on the insurance value chain has, however, changed the destiny of insurers to pay more attention to customer-centricity (PwC, 2019, p.4).

Regulators in Africa should plan measures to localise more risk at home to conform with global standards. Nevertheless, the level of regulation across the rest of the African insurance industry is not on par with global and South African markets. Some African countries only introduced risk-based models following recent developments in Europe and SA (Muguto, 2018). Notably, these forecasts were made before COVID-19 became a global pandemic. Meanwhile, global stock markets have plummeted due to the adversity of the pandemic.

Since Covid-19 was declared a pandemic by WHO on 11 March 2020, governments across sub-Saharan Africa imposed lockdown restrictions to contain the outbreak of the COVID-19 pandemic. As the pandemic disrupted businesses and governments, volatility in the global environment strained the health system and the insurance industry in general due to losses in human life, which negatively impacted sub-Saharan Africa (World Bank Group, 2020, p.3).

As the number of COVID-19 cases continued to rise rapidly, with SA leading the way, it threatened and overwhelmed sub-Saharan Africa's underdeveloped healthcare system (International Monetary Fund, 2020, p.5). Essentially, the effect of the COVID-19 outbreak retrogressed the development and progress made by sub-Saharan Africa in recent years.

Thus, damaging business and governments' balance sheets, leading to more poverty and unemployment, and retarding the region's growth prospects in the future (International Monetary Fund, 2020, p.5). Consequently, consumer trust and confidence declined, significantly reducing demand for life insurance products in sub-Saharan Africa. While sub-Saharan economic conditions brightened the outlook for the insurance industry in 2019, the life insurance business in sub-Saharan Africa contracted in 2020 as the industry responded to payment of insurance claims related to the COVID-19 outbreak (Insurance Information Institute, 2020, p.2).

It is worth noting that COVID-19 has changed our lives in ways that will impact humanity. Amidst this unprecedented crisis, a new world has emerged marked by intense competition, complexity, ambiguity, and uncertainty. Corona crisis caused global crude oil prices to fall to their lowest levels on April 20, 2020.

As crude oil prices declined 15$ per barrel worldwide, market conditions, including the financial markets, suffered from the decline of oil prices, causing a major setback resulting in both risk and opportunities for the insurance industry, regulators, and consumers to interact and maintain operations through this period (Gray & Rinehart-Smit, 2020).

Thus, COVID-19 has highlighted inefficiencies relating to products, processes, and technology along with pre-existing weaknesses in insurance markets and placed them under pressure (Gray & Rinehart-Smit, 2020). Notably, the COVID-19 outbreak has accelerated the opportunities for digital engagement and digitised delivery in the insurance industry. As the lockdowns across Africa persisted, the migration of customers from physical to digital was expected to jump significantly in the future (World Bank Group, 2020, p.24).

In sum, individuals and businesses are already wary of the insurance industry in Africa. Alas, COVID-19 has exacerbated this perception, leaving the insurance industry at an all-time low because some insurers refused to pay claims—citing that the pandemic was not covered, forcing many businesses and households to seek redress from courts. However, the resulting lack of trust provides an opportunity for the insurance industry to step up and rebuild trust while adapting to new ways of doing business. In addition, the pandemic has highlighted the lack of products available on the continent that effectively address consumers' risks and realities and the limited reach of insurance.

Therefore, insurers should foster internal innovation and external collaboration with fintech to rethink and reimagine their approach to reaching new customers and take advantage of the increasing penetration of online business, digital adoption, and the burgeoning middle-class (Muguto, 2018). Furthermore, the rapid rise in technology will enable insurers across Africa to innovate quickly and analyse customer data for designing new products (Muguto, 2018).

2.1.4 The South African Insurance

The African Development Bank (2020) estimated Africa's economic growth for 2019 to be at 3.4 percent, similar to the previous year. This growth was below the average of 5 percent for the past ten years. Despite the rest of Africa achieving stable growth in recent years, analysts predicted South Africa's (SA's) economy to recover from the 2018 short-lived recession to achieve a growth rate of 1.6 percent. Therefore, SA's growth prospects were estimated based on the notion that household income could increase together with the country's new business-friendly environment (Africa Insurance Organisation, 2019, p.13).

Similarly, Kambou and Steinbach (2019, p.110) predicted SA's growth to decline to 1.3 percent in 2019 and 1.7 percent between 2020 and 2021. Furthermore, Kambou and Steinbach (2019) pointed out that SA's slow growth in household credit extension and high unemployment constrains domestic demand in 2019. However, SA's growth has been slowing down from 1.2 percent to 0.7 percent with equity markets declining by 14 percent yearly (KPMG, 2019, p. 51). In addition, SA's high unemployment rate and hikes in fuel prices were among other factors contributing to the country's declining consumer confidence. This outlook signifies that consumer confidence is the primary driver of the life insurance spending (MarketLine, 2020).

As growth prospects in many matured markets remained modest, the pace of economic growth in the rest of Africa declined due to its over-reliance on commodities, financial and political uncertainty, and high levels of unemployment. These events have retarded growth and insurance penetration across Africa's insurance sector (PwC, 2018).

Specifically, the SA life insurance market experienced moderate growth during the historical period except for 2017, when the market deteriorated slightly due to declining consumer confidence and a weakening economy impacting household incomes (MarketLine, 2020). Consumer confidence has also likely slowed the demand for insurance and discretionary spending. In addition, SA insurers were directly affected by the recent rating downgrades, which were more likely to reduce the demand for insurance products (PwC, 2018).

Ernest and Young (2016a, p. 28) have reported that despite the economic malaise faced by SA, nearly 75 percent of all African insurance premiums were generated in South Africa. For instance, in 2016, SA alone contributed $ 42 billion, or 0.89 percent of the total written premiums global markets (PwC, 2018, p.13).

Despite Africa recording life insurance premiums of $ 44.9 billion in 2017, the SA life insurance market contracted by 0.3 percent to $ 38.3 billion, which is 85 percent of Africa's life insurance premiums. The achievement was reduced from 91 percent ten years ago, showing that other markets were slowly catching up (Africa Insurance Organisation, 2019, p.18). While Nigeria lost about 40 and 20 percent of life insurance volumes, other African markets expanded considerably, with Egypt posting the fastest growth rates, achieving 9.7 percent for the period in review (Africa Insurance Organisation, 2019, p.19).

Furthermore, the Africa Insurance Organisation (2019) affirmed that the contractions in Nigeria and SA were attributed to weaker economic environments with higher unemployment rates, thus negatively impacted on the demand for life assurance products in both countries. SA, however, remains the largest insurance market with the matured financial sector in Africa (MarketLine, 2020; Ernest & Young, 2016a).

Additionally, SA's insurance market is highly competitive and well-capitalized (Muguto, 2018; IMARC, 2020). Equally, the SA's insurance penetration rate of 11.8 percent of GDP in 2018 was very high across Africa (Swiss Re Sigma, 2018). When the SA's insurance penetration rates declined to 16.99 percent in 2017, it was comparable to other developed global markets. It then remained the most dominant in the African market, pointing toward fewer opportunities for growth (PwC, 2018, p.14).

In retrospect, the SA life insurance market attained $38.4 billion in gross written premiums in 2018, representing a Compound Annual Growth Rate (CAGR) of 3.3 percent between 2014 and 2016 (MarketLine, 2020). In contrast, the Egyptian and Nigerian insurance markets attained $0.7 billion and $ 0.5 billion and 18.2 and 31.7 percentile points, respectively (MarketLine, 2020, p.8). Moreover, the SA insurance market was expected to grow its CAGR by 7.4 percent and drive its market share to the value of $54.8 billion in 2023. Meanwhile, Egyptian and Nigerian markets were expected to post CAGRs of 21.1

and 15.6 percentile points, respectively, and $ 1.4 billion each for market values over the same period (MarketLine, 2020, p.9).

Equally, Africa Insurance Organisation (2019, p.17) found that total real premium growth was positive in Egypt with an attainment of 9.8 percent, while SA was stagnant at 0.1 percent, and Nigeria's earnings stood at -10.5 percent over the same reporting period.

Meanwhile, a moderately lower share of life insurance premiums in the region indicates that Africa lags behind the global emerging markets averages (Africa Insurance Organisation, 2019). In their report, Thom et al. (2019, p. 26) found that insurance companies in sub-Saharan Africa played a limited role in capital market development attributed to the combined size of insurance assets across the four countries investigated being less than $ 10 billion in 2016, with less than $12 billion and $ 210 billion owned and administered by the SA insurance sector.

This result showed that SA's insurance market was more mature, innovative, well-regulated and well-managed across Africa (MarketLine, 2020). PwC (2018) consistently confirmed that the SA insurance market is equipped with multi-channel distribution models and a sound regulatory environment, making it a highly competitive and more mature market in Africa.

Given the sophistication of the SA insurance market, its regulators adopted global regulatory standards earlier than other countries on the continent. Overregulation and compliance costs have exacerbated the costs of doing business in SA, inhibiting the country's future insurance growth opportunities (MarketLine, 2020; PwC, 2018).

Thus, SA insurers seek organic growth outside the country to pursue increasing insurance penetration. Despite the lower growth prospects for SA insurers, the country's life insurance GWP's rose by 22 percent to R19.3 billion in June 2017 compared to the previous year (PwC, 2018, p.16). As life insurance penetration was still shallow, insurance growth in SA was impacted by low economic growth and high levels of unemployment (PwC, 2018). Traditionally, access to insurance for lower households in SA was restricted only to funeral insurance products. However, new regulations for risk capital requirements

present an opportunity for domestic market expansion to increase penetration in the SA underinsured emerging middle-class (PwC, 2018).

For example, SA's new microinsurance framework presents opportunities to prune costs and increase access to emerging consumer segments that were not catered for under the mainstream Insurance Act and Regulations due to higher acquisition costs for this consumer segment (PwC, 2018). For that reason, SA life insurers are broadening the reach of life insurance in the country's lower-income segment (MarketLine, 2020).

Given the unique market constructs of SA's insurance sector, the life insurance market is concentrated among small, medium, and large-sized companies. The SA insurance market is competitive and is dominated by well-capitalised large companies offering differentiated products and services (MarketLine, 2020; PwC, 2018).

Equally, exit barriers in the SA insurance industry are still very low due to the regulatory system imposing capital adequacy measures preventing insurers from bankruptcy to ensure the protection of policyholders (MarketLine, 2020). Leading SA insurance companies have a strong reputation and are highly recognised by consumers. Most companies prefer mergers and acquisitions with smaller companies that lack scale (MarketLine, 2020). The entrance of large retailers and mobile operators makes competition fierce for the SA insurance industry since they have access to a large customer base and are more technologically advanced (PwC, 2018).

As insurance markets are less concentrated in sub-Saharan Africa, most SA insurance companies have pursued organic growth to acquire other companies in sub-Saharan markets (Ernest & Young, 2016a; MarketLine, 2020). The COVID-19 pandemic threatened many people's lives and collapsed the global economy, leading to most economies' collapse. For instance, Nigeria, the biggest economy in sub-Saharan Africa, was predicted to plunge by -3.4 percent due to control and pre-emptive measures (International Monetary Fund, 2020, p. 5). Furthermore, the International Monetary Fund (2020, p. 5) predicted that SA's economic growth could drop to -5.8 percent by 2020 due to a lower demand expected to compound structural problems.

Similarly, SARB (2020, p.2) revised SA's GDP growth forecast to -7 percent for 2020, citing the adverse effects of COVID-19 along with the recent revision of SA's sovereign credit rating to high risk by Moody's in March 2020.

Moreover, the SARB (2020, p.9) added that significant volatility in equity markets was reported in the Johannesburg Securities Exchange (van Griethuijsen et al., 2015), with All-Share Index losing 12 percent in the quarter of 2020. Meanwhile, the JSE's Financial Index deteriorated by 32 percent, thus resulting in some of the JSE's five listed insurers weakening between 25 and 54 percent in April 2020.

In addition, the SARB (2020) also cautioned that more jobs and household incomes could be impacted negatively while the country's financial sector would remain strained. However, it is worth noting that SA's economy was already in a recession long before the country's first case of COVID-19 was recorded. This view concurred with ABSA's Senior Economist Peter Worthington's statement that SA could not avoid rating downgrades from credit rating agencies due to the countries expanding fiscal debt deficits and slow progress with essential structural reforms.

Therefore, SA did not have much room to address the adversity of the COVID-19 crisis due to its deteriorating fiscal position and increased public debt. If the COVID-19 crises continued into 2021 and 2022, many customers could be distressed, and some businesses could be closed indefinitely with persistent job losses (Thukwana, 2020).

In addition, human lives would be lost, and poverty and inequality could rise due to the pandemic, likely contributing to social unrest and affecting economic growth. Consequently, the insurance sector would be impacted by a sharp slowdown in economic activity and lower demand for insurance products (International Monetary Fund, 2020).

Thus, the COVID-19 pandemic could significantly impact the insurance sector due to its contractual coverage of health and mortality risks (World Bank Group, 2020). Inevitably, the sector would see a rise in insurance claims and greater expenses connected with managing the claims-related benefits (World Bank Group, 2020).

While the COVID-19 pandemic has infected millions of people at an alarming rate globally, SA reported its first Covid-19 case on 5 March 2020. The country's first Covid-19 fatality was reported on 27 March 2020. Concurrently, the spike in COVID-19 infection shook SA's financial sector, and the value offered by the insurance industry in the economic resilience of firms and individuals could not be understated (Rinehart-Smit, 2020).

In response to the pandemic, SA insurers modified products to offer premium holidays and guarantees to avoid the adversity of early terminations and withdrawals. Also, SA insurers provided current and new clients with free new COVID-19 life insurance coverage (Shaw, 2020). As a result of these changes, insurers had to prepare for high costs, adjusting their budgets and cash flows to ensure that they were well-capitalized for any surge in claims to keep up with higher costs of service supply limits in the health sector (Shaw, 2020).

On the brighter side, the SA insurance industry had R373 billion in free assets, which was more than double what was needed under the country's Prudential Authority's capital requirements (Cranston, 2020). Furthermore, Cranston (2020) pointed out that policyholders would not be left stranded due to disruptions caused by the COVID-19 outbreak.

Equally important, the Association for Savings and Investment South Africa (ASISA) reported 1 588 605 death claims totalling R92 billion paid out by SA life insurers during the 18-month review period commencing on 1 April 2020 and ending 30 September 2021, which included the first, second and third waves of the pandemic. These claims constituted a 53 percent increase in death-related claims above pre-Covid levels, indicating that the third wave of the pandemic was far worse than the previous two waves.

In sum, the disruptions caused by the COVID-19 outbreaks on individuals, businesses, and economies have highlighted the significance of a sound, stable and developed insurance market and the broader role in capital market development, business, and household pliability (Rinehart-Smit, 2020). The Covid-19 outbreak has highlighted the

vulnerability of the SA insurance business and has resulted in significant changes in the climate in which insurance firms operate.

In overcoming these challenges, SA insurance companies must become more engaged in the digital economy and use big data analytics to obtain essential insights into acquiring new clients and improving their customer experience. Since the Covid-19 epidemic has not yet abated fully, it has demonstrated the capacity of SA insurance companies to innovate and establish organisational resilience to address the adversity created by Covid-19. Therefore, SA insurers should tailor business processes to consider customers, distribution channels, and employees.

With digital transformation and merging of big data and analytics to increase the accuracy of traditional CI techniques, SA's insurance market may quickly recover from the Covid-19 disaster. CI and digital transformation will enable SA insurance companies to discover new revenue prospects. Therefore, SA insurance businesses should establish clear institutional frameworks for CI to harness and unleash the potential of big data technology and techniques to incorporate such critical insights into CI activities.

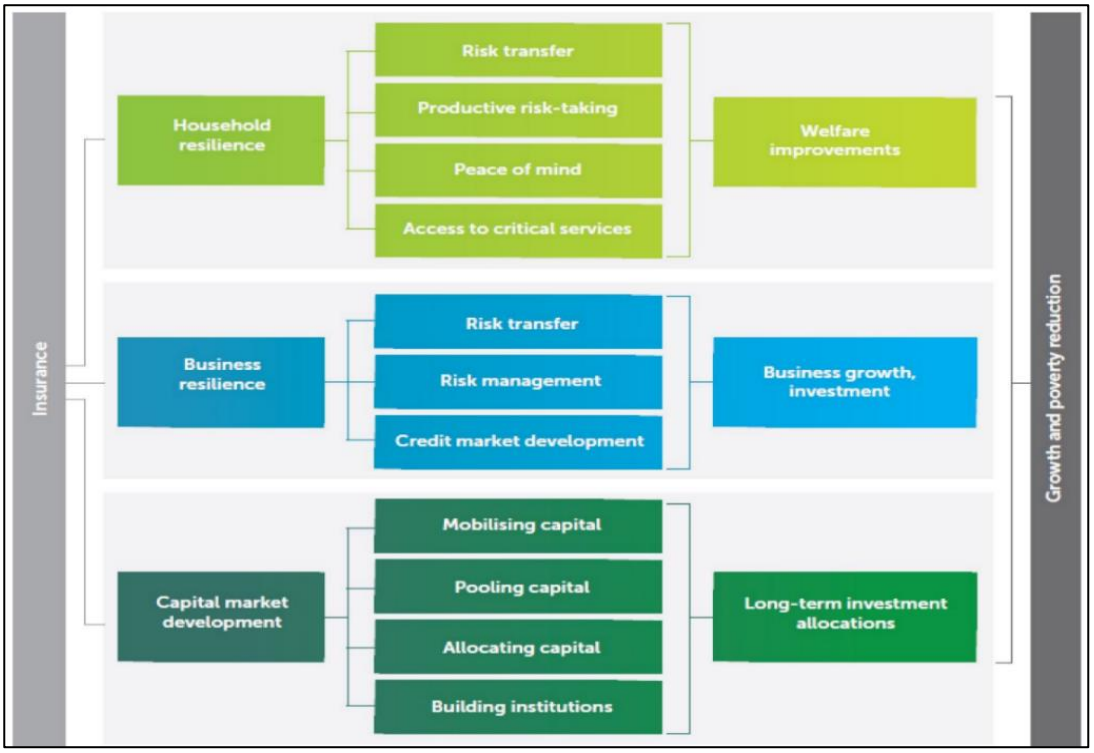
Thus, developing an integrated CIE model for the SA insurance business will help the industry get insights from behavioural economics and perform data analytics to understand consumer purchasing habits better and improve the country's economic growth.

2.1.5 The Significance of the Insurance Market

The changing global economic trends will transform the customer base for most industries worldwide. Rising per capita incomes, favourable demographics, and continuing economic growth lead to a massive expansion of the nascent middle-class (Freiling et al., 2017). Furthermore, Freiling et al. (2017) add that the development of the middle-class would be aided by financial inclusion. As uncertainty impacts personal and business activities, the financial sector has promoted economic growth (Ndalu, 2016). In essence, a country's effective and sophisticated financial system stimulates productivity and is key to economic growth (Mall, 2017).

Consistent with these views, Chamberlain et al. (2017); Msulwa, Loots, Hougaard and Bennett (2018) maintain that a well-functioning insurance market aids productive risk-taking, thereby supporting proper risk management by easing the effect of exposure to insurable risks. Meanwhile, insurance is a risk management tool primarily used to hedge risk resulting from unpredicted events (Jadoun, 2017). The importance of a sound and stable insurance market is illustrated in Figure 2.1 below.

Figure 2.1: Insurance for Growth Transmission Mechanisms



Source: Chamberlain et al. (2017, p. 3)

Figure 2.1 demonstrates that insurance improves the well-being of households; it ensures the growth of the business, while premiums collected from both businesses and individuals help to fund capital markets. Insurance companies collect premiums to share risk and enhance investor confidence and economic growth (Regupathi & Abu-Bakar, 2017).

In comparison, Jadoun (2017) maintains that insurance transfers risk equitably from one entity to another in exchange for payment. The amount to be charged for specific insurance coverage is called the premium. Financial intermediaries rally savings and provide risk management and liquidity to improve resource allocation and contribute to economic growth (Devarakonda & Chittineni, 2019).

Precisely, the insurance markets accumulate capital and dispense it into the economy to support capital market development (Chamberlain et al., 2017). Despite financial intermediaries fulfilling the function of accumulating savings into domestic investments, they distribute capital resources to reduce capital outflows and improve productivity and economic growth (Hussein & Alam, 2019). Consequently, the insurance sector provides adequate investible funds for social protection to reduce poverty, thereby increasing employment and productivity (Mir & Mishra, 2019).

Insurance is a crucial instrument used to transfer risk and intermediation (Outreville, 1990; Outreville, 1994; Outreville, 2013; Outreville, 2015). Therefore, apart from its advantages as a risk management tool, insurance mitigates financial risks arising from the insured's death (Fadun & Shoyemi, 2018). Moreover, insurance protects life and non-life events such as assets, death, disability, health, occupational injuries, retirement, road accidents, and unemployment (Leepsa & Digal, 2015).

The insurance sector also protects assets, education, and health (Mir & Mishra, 2019). Relatedly, Thom et al. (2019) advocate that insurance empowers households to gain access to credit, health, and education. Insurance prevents adversity and reduces anxiety, providing affordable health care coverage to the broader market (Gine, Ribeiro & Wrede, 2019). The above views show that insurance protects households and companies from different risks. In doing so, insurance affects economic activities in various ways (Dash, Pradhan, Maradana, Gaurav, Zaki & Jayakumar, 2018).

Meanwhile, the insurance sector has a clear social value since it serves a variety of valued economic activities with distinction emanating from sorts of financial institutions (Ndalu, 2016). This view concurs with Fashagba's (2018) idea that the insurance sector, other

than the banks, plays a vital role in raising capital to fund investments in the mainstream economy.

Beck and Webb (2003) also advocate that life insurance products boost long-term investments in public and private sector projects. Furthermore, insurance supports growth initiatives, creating demand and supply of capital to promote investment and infrastructure development (Thom et al., 2019).

Meanwhile, insurance encourages a culture of long-term savings through life insurance contracts on which accumulated premiums are used to finance government projects to inspire economic and national development and contribute to the country's GDP (Fadun, 2013; Gabriel, 2015). Notably, there is an upsurge in insurance activities in developed and developing economies due to the increased market share of the insurance sector in the financial industry (Mall, 2017; Olayungbo & Akinlo, 2016).

Olayungbo (2015) holds that there is no disparity between banks, capital markets, and insurance companies, as these sectors serve as financial intermediaries to individuals, companies, and governments. A sustainable insurance sector significantly reduces the risk for households, organisations, and the public.

In this manner, insurance provides more appropriate risk management and alleviates the impact of exposure to insurable risk (Chamberlain et al., 2017; Lester, 2014; Mall, 2017; Msulwa et al., 2018; Webb, 2006). Therefore, insurance companies are financial institutions that provide insurance services to the insured public by collecting premiums and reinvesting them in exchange for returns. Such returns play a crucial role in achieving economic and social progress (Hussein & Alam, 2019).

Essentially, the insurance industry protects against financial loss from general uncertainties likely to occur in everyday life (Sambo, 2016). While insurance is the primary provider of risk management resources for companies and individuals, it also plays a significant role in economic growth (Devarakonda & Chittineni, 2019). Insurance also covers wide-ranging risks in every human activity, such as social life and economic activity (Din, Arpah & Angappan, 2017).

Insurance markets thereby contribute to capital accumulation and intermediation of funds to the economy (Chamberlain et al., 2017). In that way, insurance and reinsurance companies provide risk cover to the insuring public; insurers underwrite insurable risks in return, collecting premiums from the insuring public, which serves as the primary source of the insurance funds (Fadun & Shoyemi, 2018). Furthermore, Fadun (2013) advocates that insurance is a mechanism used to mitigate organisations from financial losses resulting from uncertain events.

Likewise, Fashagba (2018) conversely states that insurance is a contract that manages the transfer of risk between two or more parties. Insurance contracts are thereby stable due to their nature of providing emergency funds in the occurrence of certain events compared to bonds and securities (Din et al., 2017). Essentially, insurance could be in this class, namely, reinsurance life. As such, life insurance provides funds for a long-term purpose, while non-life insurance is funding for the short-term (Mall, 2017).

Beyond just a safety net, it performs a crucial role in the social well-being of individuals by enabling them to take calculated risks that emerge from poverty and make provisions for their families in case an unforeseen event occurs (Freiling et al., 2017; Fashagba, 2018). This points toward insurance playing a vital role other than circumventing the unpredictability of economic conditions (Chau, Kin & Teng, 2013). For that reason, insurance companies remain among the most influential investors, contributing significant business volumes to the economy (Lee, Lee & Chiou, 2017).

Similarly, Mall (2017) advocates that insurance companies, mutual, and pension funds invest immensely in capital markets. Furthermore, she opines that factor such as the ageing population, globalisation, and inequality impact economic development.

In addressing economic development, the insurance sector accumulates premiums and underwriting profits from the insured to invest in capital and financial markets to contribute to the country's economic growth (Olayungbo, 2015). The insurance business also plays a critical role in sustaining and supporting growth by deploying long-term capital in the mainstream economy and protecting both households' and corporates' economic and social assets (Chamberlain et al., 2017).

Furthermore, insurance provides income financing for various investments in the local market (Hussein & Alam, 2019). Insurance facilitates investment and provides risk management services for easy economic consumption (Lee, Cheng, Nassir & Ab Razak, 2018). Consequently, insurance plays a critical role in the growth of the economy (Fadun & Shoyemi, 2018).

As insurance generates assets from the premiums paid by the life insured to fund capital markets (Fashagba, 2018; Olayungbo, 2015); the capital pool arising from the collection of life insurance premiums is deployed in various nation-building activities that enhance economic growth (Dam, 2017). Insurance companies create assets from claims invested in the capital markets to contribute to economic growth (Ndalu, 2016; Olayungbo, 2015).

Thom et al. (2019) also point out that the insurance markets contribute to economic growth depending on the country's development. Likewise, in Greenwood and Jovanovic's (1990) view, some countries are still in the early stages of development, citing that they do not have a developed insurance market. The insurance market's growth and development depend on the economy's expansion. This view signifies that the insurance market follows the S-curve, which varies for every country and economy, driven by different income elasticities (Greenwood & Jovanovic, 1990; Enz,2000; Regupathi & Abu-Bakar, 2017).

Thus, a growing insurance market supports the economic development (Thom et al., 2019). In line with this view, Han et al. (2010) maintain that another significant role performed by insurance development is related to early development in many countries. This shows that insurance market development is a strong predictor of economic development at different stages of development in various countries (Webb, 2012 cited in Chamberlain et al., 2012, p.3).

In brief, insurance markets play a vital role in risk mitigation and intermediation. In so doing, insurance preserves assets and mitigates financial shocks for individuals and companies (Chamberlain et al.,2017; Devarakonda & Chittineni, 2019). Additionally, the insurance sector accumulates premiums for long-term investments in capital markets and

nation-building activities to augment economic growth (Chamberlain et al., 2017; Dam, 2017).

The insurance sector promotes financial stability to equity markets and provides instruments to transfer the risk from businesses and individuals to insurers. Therefore, the insurance industry stabilises and diversifies risk, contributing to the country's national economic development (Fadun & Shoyemi, 2018). In developed economies, the insurance market is saturated with no room for growth.

However, the outlook for the insurance market is promising, driven by more demand and lower insurance penetration rates in developing economies, thus presenting an opportunity to pursue growth in these active markets, which are rapidly expanding and ready to contribute significantly to economic growth (Dam, 2017). Considering that insurance markets play a vital role in the economy, it is necessary to examine the causative connections between insurance and growth in the next section of the empirical literature.

2.1.6 Insurance and Economic Growth: What's the Connection?

Insurance, like banks and the financial markets, plays a critical role in sustaining global economic growth (Din et al., 2017). The insurance industry is part of the monetary value chain, influencing the demand side of economic growth, and it is vital to the country's financial success (Chang, Lee & Chang, 2014; Chau et al.,2013; Lee, Lee & Chiu, 2013; Malloy, Pearson-Merkowitz & Morris, 2016; Outreville, 1990; Pan & Su, 2012; Pradhan, Arvin, Norman, Nair & Hall, 2016).

These views signify that the insurance market improves financial integration through risk transfer and indemnification among countries (Sufian & Kamarudin, 2016). In essence, insurance supports the country's financial sector's development by enabling long-term investments and employing innovative ways of facilitating trade for individuals and companies to gain access to financial markets (Lester, 2014). Insurance protects against business risks, thereby aiding businesses to operate cost-effectively to sustain themselves and contribute to economic growth (Nielsen & Balarezo, 2017).

Without insurance, organisations should liquidate their assets and pay for unpredictable losses from their operating budgets. As a result, the importance of insurance for individuals, corporations, and governments cannot be under sated (Regupathi & Abu-Bakar, 2017). Insurance supports risk-taking behaviour in a society susceptible to economic activities (Olayungbo & Akinlo, 2016).

Equally important, insurance reduces risks and preserves much-needed resources to cope with uncertainty during turbulent times. Insurance also promotes economic growth and entrepreneurship through financial intermediation (Carson, Chen, Outreville & Icer, 2014; Cristea, Marcu & Cârstina, 2014; Outreville, 1990; Outreville, 1994; Outreville, 2013; Outreville, 2015).

Insurance, in essence, promotes creativity, innovation, entrepreneurship, and commerce, all of which are critical for economic growth (Billah, 2014; Cristea, Marcu, & Cârstina, 2014). The market share of the insurance industry has continued to increase with an average growth rate of 10 percent higher than the overall global economic growth since 1950 (Haiss & Sümegi, 2008; Lee et al.,2013).

Consistently, there has been an upsurge in insurance market activities in developing economies due to financial liberation and integration (Chang et al., 2014b). This is attributed to a surge in insurance spending of 8 and 11 as well as 2 and 4 percent in developed and developing economies (Din et al., 2017; Outreville, 2013). The Swiss Re Sigma (2016) report has also indicated that the insurance sector contributed 6.23 percent of the global GDP. This result shows that the insurance sector is a catalyst for the financial system of the country (Pasiouras & Gaganis, 2013).

The banking sector and the financial markets operate similar to insurance, providing long-term savings (Haiss & Sümegi, 2008). It offers protection against any risk event by improving productivity in tandem, contributing more significant investments to economic growth (Ghosh, 2013). Based on the above, insurance ensures economic and financial stability. Insurance diversifies risk and promotes savings in the mainstream economy (Haiss & Sümegi, 2008; Han et al.,2010; Lee, Chang, Arouri & Lee, 2016).

While insurance is perceived as a complementary service, it should be considered a substitute for stock markets (Chen, Lee & Lee, 2012). Even so, some research studies in this field only focused on the role played by the banking and stock market in promoting economic growth (Horng, Chang & Wu, 2012).

Most studies did not investigate the insurance sector and other financial institutions (Haiss & Sümegi, 2008; Njegomir & Stojić, 2010; Verma & Bala, 2013). Given that the insurance market plays a positive role in the global GDP, the causative relationship between insurance and economic growth has become significant in developed and developing countries financial stability (Olayungbo, 2015).

Consequently, the insurance contribution to certain countries' GDP reaches over 12 percent of the market share in economic activities (Cristea et al., 2014). This result signifies that countries that experience an upsurge in economic developments will gain more market share in insurance activities (Cristea et al., 2014).

Hence, some studies reported that insurance and economic growth relationships were country-specific and dependent on several economic activities (Dash et al., 2018). So economic growth should be the main determining factor in life insurance consumption in countries (Kaabia, Goutte, Guesmi, Dhaoui & Abid, 2019).

Essentially, the insurance sector encourages economic growth and prevents sudden and devastating occurrences in developed and developing countries (Iyondo, Samuel & Inyanda, 2018). Furthermore, Iyodo et al. (2018) mention that globally and locally, the insurance sector was linked to other sectors of the economy. Meanwhile, its significant economic activities and improving the means of support for humans and business have grown.

Various studies have proved that the insurance industry's growth was connected to economic growth and that insurance provided income security for individuals and companies (Tom, Ibok & Awok, 2014; Ward & Zurbruegg, 2000; Webb, 2006). Thus, the insurance sector contributes positively to economic growth in different geographies and sections of the mainstream economy (Yinusa& Akinlo, 2013; Zouhaier, 2014).

Concurring, Ward and Zurbruegg (2000) revealed a supply-leading pattern for some countries. Also, a demand following the connection between insurance and economic growth was discovered in other countries (Ching et al., 2010). Pan and Su (2012) also showed a significant demand following pattern insurance sectors in high-net-worth provinces across China, with a supply-leading pattern prevailing throughout most provinces at different development stages.

However, there were significant patterns in China's low-income provinces. In contrast, Ward and Zurbruegg (2000) discovered insignificance between insurance and economic growth for the UK and US among Organisation for Economic Co-operation and Development countries studied. Similarly, Regupathi and Abu-Bakar (2017) indicated that a country's insurance demand followed a pattern. *Per se*, the disparities in the relationship between insurance and economic growth were found in different countries and economic environments.

This result signifies that insurance activities are diverse in different income groups. For example, previous research studies by Arena (2008) and Haiss and Sümegi (2008) demonstrated that life assurance was prevalent in developed and developing countries. In contrast, short-term insurance is prevailed in developing countries and contributes significantly to economic growth. Congruently, a study by Iyodo et al. (2018) found that short-term insurance penetration had a significant effect on the Nigerian economy.

An investigation by Pan and Su (2012) found that insurance significantly contributed to the economy in developed provinces. Conversely, Alhassan and Fiador (2014) established that both life and short-term insurance had a 10 percent contribution to fiscal expansion in Ghana. Furthermore, their study found that non-life insurance penetration was the highest compared to life insurance.

Fadun and Shoyemi's (2018) findings indicated a positive correlation between total insurance investments and the monetary increase in Nigeria. Also, Fashagba (2018) found a causative and insignificant relationship between non-life insurance and negative associations. Furthermore, this study showed the significance between life insurance and fiscal expansion.

These results signify those premiums collected from non-life business activities translated into higher economic growth than premiums from life business activities (Arena, 2008; Haiss & Sümegi, 2008). Din et al. (2017) disclosed that life insurance positively correlated with economic growth in developed countries.

Consistently, other studies found that life insurance was associated with economic development in developed economies (See Arena, 2008; Alhassan, 2016; Ouedraogo, Guerineau, Sawadogo & Relwende, 2016). In addition, Din et al. (2017) highlighted that short-term insurance was meaningful for developed countries when evaluating density.

These results concurred with Chang et al. (2014b), Focarelli (2017), Kjosevski (2012), and Lee et al. (2016b). Net written premiums and penetration varied little with fiscal expansion when proxied by the insurance industry (Impavido, Musalem & Catalan, 2000; Tong, 2008; Umoren & Joseph, 2016; Ward & Zurbruegg, 2000). These results corroborated the studies of Alhassan and Fiador (2014), Webb, Grace and Skipper (2017).

In the short run, Regupathi and Abu-Bakar's (2017) findings revealed a strong and favourable association between short-term insurance and monetary growth for China, India, Malaysia, Pakistan, the USA, and the UK. They also found a negative correlation between life insurance and China's, Malaysia's, and the US's fiscal. In contrast, Zouhaier's (2014) analysis showed an encouraging effect on short-term insurance penetration rates but an adverse effect on total insurance in developing countries.

Moreover, Ward and Zurbruegg (2000) highlighted that income discrepancy influenced different insurance behaviours amongst countries. Therefore, when evaluating the correlation between insurance and fiscal expansion, it is essential to consider income differentials (Arena, 2008; Haiss & Sümegi, 2008; Han et al.,2010; Pan & Su, 2012).

Similarly, literature has shown evidence of positive relationship between insurance and economic growth (See for example, Akinlo, 2013; Alhassan & Fiador, 2014; Arena, 2008; Dam, 2017; Dhiab & Jouili, 2015; Eze & Okoye, 2013; Fadun, 2013; Hussein & Alam, 2019; Ndalu, 2016; Sambo, 2016; Verma & Bala, 2013).

In contrast, some authors like Haiss and Sümegi (2008), Kaabia et al. (2019), Lee et al.(2016a), Omoke (2012), among others, have established a negative relationship between insurance and economic growth or no relationship at all. Thus, insurance dampens economic growth. For instance, if insurance companies bear the average risk due to the insured not taking accountable preventative measures to safeguard assets, the risk exposure is likely to increase.

In essence, the insured actions dampen economic growth resulting in insurance companies providing more risks to cover rather than investing in the economy (Cummins & Doherty, 2006). This opinion suggests that securitisation through a selection of insurance can adversely affect the economy (Haiss & Sümegi, 2008). Furthermore, Haiss and Sümegi (2008) have pointed out that ethical risks likely increase insurance penetration rates.

In addition, several studies found mixed results—showing both significant positive and negative correlations between insurance and economic growth (Akinlo, 2013; Alhassan, 2016; Ching et al.,2010; Dash et al.,2018; Lee et al., 2013; Olayungbo, 2015; Olayungbo and Akinlo, 2016; Otsile et al.,2018; Pradhan et al., 2016; Regupathi & Abu-Bakar, 2017; Yinusa & Akinlo, 2013). Conversely, Umoren and Joseph (2016) found that insurance premiums had a positive effect on GDP growth but behaved insignificantly to the contribution made by the insurance industry to the Nigerian economic growth.

Previous research studies have also highlighted that the role of insurance in promoting economic growth was not continuous as in certain instances and thereby had an insignificant role in developed economies (Arena, 2008; Haiss & Sümegi, 2008; Han et al., 2010; Pan & Su, 2012; Ward & Zurbruegg, 2000).

Meanwhile, the negative correlations between insurance and monetary expansion have been attributed to different proxy measures of insurance activity and density in these countries (Din et al., 2017). Even with insurance playing an insignificant role in developed economies, the increasing share of the insurance industry in developed and developing countries has attracted more interest in the insurance and growth relationship (Iyodo et al., 2018).

Olayungbo (2015) mentions that even with reforms in the insurance sector not affecting economic activity, its growth positively impacts economic development. Pearson (2010), therefore, advocates that more comparative studies are required to understand the causative relationships between insurance and economic growth to generalise these studies.

Yinusa and Akinlo (2013) also maintain that most of these studies come from prolific authors from the U.S., U.K., and Nigeria, in which their study results were consistent. Consequently, very few studies are conducted in developing countries, as many tried to examine Africa's insurance and economic growth (Olayungbo & Akinlo, 2016).

Considering that insurance positively influences economic growth, it behaves insignificantly in explaining the contribution made by the insurance industry to the Nigerian economy for the period in review (Umoren & Joseph, 2016). Congruently, Umoren and Joseph (2016) discovered that the growth in the insurance sector contributed significantly to the economic growth in Nigeria (Yinusa & Akinlo, 2013). Yet, Umoren and Joseph (2016) found in their study that claims expenditure harmed the country's economic growth.

In contrast, Omoke (2012) found a negative significance between insurance and Nigerian economic growth, and his results indicated that there was low insurance market activity and development in Nigeria. Conversely, Fadun and Shoyemi (2018), and Sambo (2016) demonstrated a strong correlation between total investment and the country's economy. Sambo (2016) then recommended that the country increase the insurance industry portfolio to maximise investments and economic development.

Iyodo et al. (2018) showed that short-term insurance penetration had a favourable and considerable influence on Nigeria's fiscal. Iyodo et al. (2018) additionally maintain that the insurance industry will significantly influence the Nigerian economy if the government can enforce and implement policies to promote insurance coverage, mainly in non-life and health insurance. Pertaining to South Africa, Ellyne and Cheng (2014) investigated the cost of a deposit for insurance premiums in SA large banks. This study's results

showed that insurance premiums held by banks were volatile over time but were comparable to international norms.

While the insurance sector has become a major component of the developed economies, the literature on this subject highlights that the insurance sector is allied to other sectors of the economy, thereby contributing to the growth of developed and developing economies (Arena, 2008; Chang et al.,2014; Ćurak et al.,2009; Verma & Bala, 2013).

With increasing incomes that give rise to assets' expansion, the insurance sector plays a critical role in hedging the risk against the increasing volatility (Jadoun, 2017). Insurance thereby reduces uncertainty by facilitating investments in the economy through risk-sharing and transfer (Han et al., 2010). This opinion signifies that insurance development plays a greater or a lesser role depending on the country's cultural and religious traditions (Cristea et al., 2014).

Yet, Cecchetti and Kharroubi (2012) contend that financial development can affect its growth and industry. Furthermore, these authors highlight that the level of economic development in advanced and emerging economies is likely to drag productivity over the long run due to the financial sector competing for similar resources with other sectors of the country's economy. Equally, the country's economy can be affected negatively due to poor customer demand for liquidity in the market, which is likely to reduce investments and economic growth (Oitsile et al., 2018).

This view shows that if a large proportion of insurance assets are invested in a foreign country, the savings substitution effect of a country will be hugely impacted by adverse economic growth (Lee et al., 2016a). Meanwhile, the development of the insurance sector facilitates investments and savings used for capital formation to induce economic growth (Alhassan & Fiador, 2014; Haiss & Sümegi, 2008; Lee et al., 2013b; Ward & Zurbruegg, 2000; Webb et al., 2017).

Impavido et al. (2000), Pan and Su (2012), and Ward and Zurbruegg (2000), however, opined that insurance sector development is an outcome of economic growth, thus suggesting that the demand for insurance products is dependent on economic growth.

Moreover, Pan and Su (2012) contend that the development of the insurance sector and economic growth are not dependent on each other. In contrast, Ghosh (2013) has also observed an interdependence between insurance and fiscal expansion.

In sum, although the country's economy is made up of various sectors, the insurance sector continues to play a significant role in promoting savings and investments, providing stability in financial markets while managing both the financial and social risks to aid the economic development of a nation (Leepsa & Digal, 2015). In so doing, insurance facilitates capital transformation, efficient pricing, and risk hedging to improve economic development and growth (Din et al., 2017). However, Africa's insurance markets are not yet established except in SA, where insurance presents an opportunity for insurance development to promote economic growth (Muguto, 2018).

Given Africa's lower insurance penetration, complex challenges that continue to deter growth need urgent attention. Insurance promotes economic progress, so African governments should develop strategies to encourage its development. In doing so, policymakers and regulators should address issues that dampen insurance penetration and leverage best practices to accelerate growth. It may also be possible to improve the economic worth of the insurance industry by introducing new product lines in saturated insurance markets like those in SA, thereby seeking organic growth prospects in other regional markets across the continent.

2.2 The Impact of Competitive Intelligence on Organisations

The recent changes in the global economy have created more challenges whereby countries face severe recession that threatens to turn into a depression as both developed and developing nations are experiencing a collapse of market conditions due to the severity of the endemic of COVID-19. While COVID-19 has created disruptions in organisations, these changes have advanced disruptive innovation, thus urging organisations to seek areas and markets that will sustain them during unprecedented times. These challenges, as never before, have highlighted the significance of CI in identifying emerging trends that are likely to change the destiny of organisations.

Essentially, organisations now need to stay on top of market changes prompted by aggressive competitive activity; so, the need for speed and agility post-COVID-19 pandemic has increased CI demand. Consequently, organisations need to perform strategic planning activities such as resource analysis, goal and strategy formulation, and organisational or systems design to cope and survive these unprecedented times (Sewdass, 2012, p.1).

Organisations, therefore, need to strengthen their capabilities and intelligence about the dynamic business environment to compete and survive in the modern world (Hamad & Yozgat, 2017). An organisation and its supply chain need agility and flexibility to respond proactively to environmental dynamics (Samantra, Datta, Mishra & Mahapatra, 2013).

Lately, disruptive innovation demands organisations to introduce new ideas, products, and services to sustain themselves in the rapidly evolving business environment (Rajnoha & Lorincová, 2015). Additionally, organisations need a variety of competitive assets to survive in the fiercely contested business environment (Hamad & Yozgat, 2017).

As part of the needs, previously used business analytics techniques should be employed to identify potential threats, opportunities, and best practices from large quantities of business data and to compare their performance against any competition (He, Shen, Tian, Li, Akula, Yan & Tao, 2015). In doing so, organisations utilise the CI function to analyse vast amounts of internal and external data to assure the quality and objectivity of intelligent information and perform different strategic planning activities (Wagner, 2003, p.70).

Specifically, CI transforms competitor information into actionable insights that allow organisations to adjust their plans to stay ahead of the competition (Tuan, 2016). CI enables organisations to benchmark their performance against the competition and focus efforts on improving efficiencies, scale, and coordination to outperform peers (Bose, 2008; Sanderson, 2013b). Mohsin, Halim and Ahmad (2015) maintain that CI inspires innovative performance; and that CI creates innovative ideas and is critical in today’s unstable global business environment. This view signifies that CI stimulates innovation and promotes agility in the organisation's (Tuan, 2016).

Importantly, CI is a suitable tool that supports decision-makers. It provides a competitive advantage to organisations in a fiercely contested business environment (Fleisher & Wright, 2009). CI also deals with the organisation's competitive environment to identify new threats and opportunities (Sassi, Frini, Abdessalem & Kraiem, 2015; Wang & Borges, 2013).

Notably, CI analyses competitive and market information to create organisational knowledge (Chevallier, Laarraf, Sébastien, Miloudi & Salvetat, 2016). CI is, therefore, a tool that complements the relationship between information and knowledge (Elbashir, Collier, Sutton, Daven & Leech, 2013). Essentially, CI can integrate and structure information and knowledge, which means that CI influences and promotes knowledge management in organisations (Chevallier et al., 2016).

This notion signifies that CI is a process that produces and transforms information into knowledge and converts information into intelligence (Prescott, 2001). CI sources external information for the organisation's decision-makers (Ross et al., 2012). In this manner, CI analyses data collected from competitors and the complex business environment to augment effective learning, and decision-making, identify market trends and predict competitor actions and anticipated moves (Tahmasebifard & Wright, 2018).

Furthermore, CI interprets information from customers and suppliers to gain insights about emerging trends that will improve the agility and flexibility of the organisation and its supply network to adjust its strategies quicker than the competition (Tuan, 2016). In that way, organisations will be prepared to respond to competitors' dynamic activities in their markets (Tuan, 2016).

Uzoamaka et al. (2017a, p.105), and Uzoamaka et al. (2017b, p. 87) also stress that CI is professed to use modern information technology systems to fast-track strategic decision-making and fulfil the current needs of organisations. Therefore, CI benefits organisations of all types and is used widely within different functions in the private and public sectors (Stenberg & Vu-Thi, 2017). Inevitably, organisations use CI to evaluate the competencies of current and potential competitors to withstand their competitiveness (Calof & Wright, 2008; Tuan, 2013).

CI, therefore, anticipates threats and enables organisations to identify opportunities in the external environment (Adidam et al., 2012). It creates new growth opportunities, allowing organisations to respond rapidly to changes in the competitive environment. Moreover, CI identifies potential vulnerabilities earlier for organisations to improve the quality of their strategic planning processes (Bose, 2008; Chen, 2010; Ross et al., 2012).

In essence, organisations that adopt CI in their business processes successfully identify opportunities and avoid threats to address competitive dynamics early (Uzoamaka et al., 2017a; Uzoamaka et al., 2017b). This view signifies that organisations seeking sustainable competitive advantage need intelligence about opportunities and threats in the global competitive environment (Johannesson & Palona, 2010).

Succinctly, competitor information is essential for tactical and strategic decision-making in organisations. However, organisations are losing the importance of collecting relevant information and knowledge to make strategic decisions about industries where they operate due to large volumes of currently available data (Stefanikova, Rypakova & Moravcikova, 2015). Additionally, most organisations still struggle to collect quality and useful competitor information because they do not have an integrated intelligent system that collects and analyse competitor data (Gračanin, Kalac & Jovanović, 2015, p.27).

CI is the integrated intelligence system that provides valuable information for tactical and strategic decision-making in the modern competitive business environment (Gračanin et al., 2015). Since data is accessible globally from public platforms, this trend changes the complexity of CI and technological advancements, presenting an opportunity for organisations to develop robust decisions.

In this manner, organisations have created functions that consist of a team of experts acquainted with collecting and integrating intelligent information, using a synergistic system that integrates CI (Bulger, 2016, p.64). Furthermore, Bulger (2016) affirms that this team would identify myriad opportunities provided by data to solve complex problems and create opportunities for organisations to be market leaders. In comparison, Tuan (2013a) contends that CI should be accumulated widely by all functions within the organisation.

Concurring, Adidam et al. (2012) uphold that human intelligence sources are relationship-based and should collect CI; therefore, CI is founded on understanding the differences between information and intelligence (Sewdass, 2012). Understanding these differences will then assist organisations in retaining and serving their markets and clients in the future. In doing so, organisations can perform predictive analytics on client data to determine the likelihood of competitor actions and gain a share of their customers and markets (IBM, 2015).

CI produces useful information, actionable knowledge and insights for organisations to solve complex problems and survive in the knowledge-intensive business environment (He et al., 2015). CI is, therefore, an activity distinct from market research since it serves a disparity of business functions (Adidam et al., 2012). CI also empowers managers of organisations to make decisions across business functions (Gračanin et al., 2015). Consequently, CI analyses information and translates it into knowledge about competitor actions for making strategic decisions in various divisions of an organisation (Adidam et al., 2012).

CI affects organisations worldwide, and it is not an activity that is prevalent only in developed countries or organisations in specific industries (Muller, 2005). With the rapid growth of competitiveness expected to spill over to organisations globally, CI is expected to play a vital role in development in the coming years, even though it will progressively be a challenge for emerging economies (Canongia, 2007, p.58).

The next section of the literature review explores CI practices in emerging markets in this context.

2.3 Competitive Intelligence in Emerging Markets

Today, as more organisations adopt emerging technologies and battle the COVID-19 pandemic, organisations in emerging economies face increased environmental uncertainties compared to their global peers (TechnologyTimes, 2020). In response to these rapid changes, they use CI to enhance their competitiveness and adapt to the changing operational dynamics (Du Toit & Sewdass, 2015).

With CI becoming a business imperative for organisations to compete successfully in the global economy, it might be difficult for organisations in emerging economies that have adapted CI practices to extend organised CI practices by global standards (James, 2000; Du Toit & Strauss, 2010; Kalinowski, 2012). For organisations in emerging economies to compete globally, technical training and major investments in information system infrastructure and services will improve the current position of organisations operating in developing markets (Sewdass, 2012).

Organisations in emerging economies should therefore employ CI practices in their business processes to gain a larger proportion of the market and compete successfully against the local and global competition (Pellissier & Kruger, 2011). In so doing, developing economies should apply CI to compete in the global economy (Du Toit & Sewdass, 2014,p.3).

CI activities in many countries oblige organisations to look beyond internal business processes, integrate events in the external environment, and translate them into an intelligent information (Strauss & Du Toit, 2010, p.304). According to Adidam et al. (2012, p.243), most of the CI literature was conceptually developed in developed markets, with the US and Europe leading with the number of publications (Søilen, 2013; Du Toit, 2015).

Research studies from developing markets have consistently found that CI practises were country-specific due to the culture and markets chosen by organisations operating in these countries (Adidam, Gajre & Kejriwal, 2009; Changhuo, Qingjiu, Luhong & Shan, 1998; De Pelsmacker et al.,2005; Flint, 2002; Muñoz-Cañavate & Alves-Albero, 2017; Singh et al., 2012; Tao & Prescott, 2000; Vidigal, 2013).

Thus, countries that foster a culture that values information and intelligence, like Asia and Europe, have acquired distinctive advantages from CI practices (Viviers et al., 2005, p.577). Most organisations in developed countries have then engrained CI functions that monitor competitor actions and activities (Du Toit, 2013). However, organisations in developing countries are overwhelmed by undesirable environmental changes, and managing intelligence is yet unknown in these countries' (Nasri, 2011, p.58).

Furthermore, Strauss and Du Toit (2010b) added that organisations in African countries, including SA, have continued to be astonished by disruptions brought by the changing business environments and are still lagging in managing intelligence by global standards.

Dou and Manullang (2004, p. 114) likewise indicated in their study that although there was awareness of CI practices and tools in countries and organisations, these practices were easily transferable to developing countries. In addition, these authors revealed that CI cultural context must be carefully analysed in developing countries to understand the existing business culture.

Even if CI practice in SA became more sophisticated and gained traction since 2002, the outlook in other African countries worsened (See for example, Du Toit & Strauss, 2010; Sewdass & Du Toit, 2014; Du Toit & Sewdass, 2015). Dou, Dou and Manullang (2005) have recommended that developing countries design a national CI system to create intellectual capital, transfer knowledge to the industry, and attract Foreign Direct Investments (FDI). Furthermore, Dou et al. (2005) indicated that China, Korea, India, Indonesia, Japan, and Morocco have invested in CI systems.

To ensure that CI is adopted and used successfully throughout the regions, leaders should foster a culture of competition and knowledge by unpacking the benefits of CI techniques in Africa (Du Toit & Strauss, 2010). While CI activities in SA have gained some traction over the years, the country's CI activities are not on par with Canada, Japan, and the USA (Viviers & Muller, 2004, p.59).

Heppes and Du Toit (2009, p. 50) corroborate the above view by stressing that even as CI activities in SA have gained momentum and developed from the business sector, they are still lagging behind Australia, Canada, France, and the US. However, big corporations in SA have adopted CI and set up structures and staff that support it, as confirmed by the previous research (Muller, Saayman, Viviers & Calof, 2002, p.30). In contrast, Viviers and Muller's (2004, p. 53-67) study found that SA companies did not have adequate structures to conduct CI practices. As such, very few SA companies had well-established CI units and systems but were fond of collecting information without being analysed.

This view signifies that SA organisations are less dynamic and resistant to change than organisations in developed countries (Sewdass & Du Toit, 2014, p.198). Moreover, Sewdass and Du Toit (2014), and Pellissier and Kruger (2011) found that CI in SA was used to be informed about government legislation changes while it was crucial to be informed of potential threats and opportunities resulting from domestic and global trends.

Consistently, the study by Du Toit (2013) found that whilst there was a culture of competitiveness amongst organisations in Brazil and SA, CI was not conducted effectively. Additionally, this study highlighted that SA organisations used CI to keep abreast of information relating to changes in regulation, although Brazil used it for operational risk. CI activities extend beyond analysing competitor actions, including regulatory matters, customers, and suppliers (Du Toit & Strauss, 2010, p. 22).

Besides gathering and analysing, CI transfers intelligence concerning competitors, customers, and products (Mabe et al., 2019). The study by Du Toit and Sewdass (2015) consistently exhibited that CI was more mature in SA than in Brazil though only a limited number of functions in both countries recognised the importance of CI in their respective organisations. In contrast, Du Toit and Sewdass's (2014a) study in Brazil, Malaysia, Morocco, and SA found that information was obtained from direct customer feedback and corporate websites due to countries not using advanced analysis techniques.

Another study by Du Toit and Sewdass (2014b) still found that organisations in Morocco implemented CI successfully, although it was not used for decision-making. This result signifies that Morocco has invested immensely in CI systems and programs that enhance organisations' competitiveness (Dou et al., 2005). In contrast, SA struggles to address skills shortages and increase its competitiveness (Sewdass & Du Toit, 2014).

With CI being a new concept in the South African work environment, no framework currently defines adequate skills for CI practitioners to succeed in their roles (Mabe et al., 2019). SA organisations are thereby very susceptible to unpredictable threats, and they are often inward-looking (Adidam et al., 2009b).

Previous research by De Pelsmacker et al. (2005) showed that organisations that used CI amongst Belgian and South African exporters could anticipate opportunities and threats in the competitive environment. Another research by Du Toit and Begg (2007) found that a mass retail import South African organisation embraced CI, even though its practices were informal.

Consistently, Fatti and Du Toit (2013) identified that even if culture was lagging, there was a sustainable commitment to the practices and principles of CI in the SA pharmaceutical industry. This result shows that most organisations have at least formal or informal CI activities to monitor the external environment (Ching & Zabid, 2017).

CI inspires innovation and global competitiveness for organisations to thrive in the new economy. There is the greatest need for SA organisations to embrace CI to enhance the country's competitiveness in the global economy (Du Toit & Sewdass, 2015). Previous research by Du Toit and Strauss (2010) has indicated that even as CI activities in SA organisations existed for at least five years, they did not yield to the country's competitive position.

With SA's competitive business environment fiercely contested, technological advances are confounding compared to global peers. For that reason, global companies in SA face unique CI challenges since they need to embed their CI programs to operate seamlessly and compete efficiently worldwide (Viviers et al., 2005, p.251-252). Muller et al. (2002) previously found that SA organisations were very poor in organising and processing CI activities. Yet, SA continues to rank low globally in terms of competitiveness (Sewdass & Du Toit, 2014).

In sum, organisations are taking advantage of their big data analytics to develop critical insights that give them a competitive advantage (Mikalef, Krogstie, Pappas & Pavlou, 2020, p.1). With big data-related technologies likely to continue in the post-COVID-19 pandemic, organisations must focus their resources on tools to manage and interpret big data for effective decision-making (Mikalef et al., 2020). Therefore, organisations should obtain internal and external information to anticipate uncertainties and monitor competitor actions.

This view shows that CI is no longer a tool that manages the environmental context. It shares knowledge strategically with the organisation's supply chain and its competitors (Chevallier et al., 2016). CI provides strategic and tactical decisions concerning understanding the technological environment, customers, and markets (Du Toit, 2015; Vriens & Søilen, 2014). In addition, organisations with a formal CI function surpass the competition since CI is the core of the organisation's strategic management (Du Toit, 2015, p.16).

Essentially, CI's involvement in knowledge management augments offensive and defensive strategic market choices and options to attack or protect against competitor actions (Chevallier et al., 2016, p.1196). The purpose and practices of CI focus on the external environment to provide early warning for effective decisions (Du Toit, 2015; Vriens & Søilen, 2014).

CI is forward-looking and performs analytical techniques for strategic decisions, thus making it like foresight (Calof, Arcos & Sewdass, 2018; Calof & Smith, 2010). Therefore, CI enhances the organisation's competitive advantage and cooperation (Chevallier et al., 2016). Equally, the size of an organisation influences its investments in resources and the development of an efficient CI program (Garcia-Alsina et al., 2016).

The study by Nenzhelele and Pellissier (2014), however, showed that SMEs' large corporations experience similar challenges in implementing CI. Thus, CI is implemented successfully if an organisation exhibits a culture of competitiveness, and more awareness is needed using the benefits of CI programs for the organisation's long-term sustainability (Pellissier & Nenzhelele, 2013).

While most organisations attempt to develop their CI capacity in the industry, SA organisations should establish formal CI functions used continuously in strategic decision-making (Fatti & Du Toit, 2013). This requires SA organisations to thoroughly adopt CI practices to enhance competitiveness in the global economy.

2.4 Conclusion

This chapter discussed the contextual and systematic factors that impact the SA and the global insurance industry and the significance of CI in emerging markets and organisations. The global insurance market was discussed, focusing on Asia-Pacific, Europe, and the United States of America. In contrast, the discussion about the African insurance market focused explicitly on South Africa, Egypt, and Nigeria. This chapter discussed the contextual and systematic factors impacting the global insurance industry, including CI, in emerging markets.

The next chapter deals with the literature review and theories from previous research studies.

Chapter Three: Theories and Models Explaining the Application of Competitive Intelligence

3.1 Introduction

This chapter comprehensively reviews the theories and models that integrate CI. This chapter covers five sections, including the systematic literature review, which examines past empirical studies on the concept of competitive intelligence. The first section discusses theory and models about how information is codified into the competitive intelligence process.

The second section illustrates theories and models underpinning strategy management and links them to competitive intelligence. The third section examines theories and models about the relationship between competitive intelligence and strategic management.

The fourth section deals with theories and models demonstrating the relationship between competitive intelligence and sustainable competitive advantage. Lastly, an empirical review and previous research findings on competitive intelligence and its effect on strategic management and sustainable competitive advantage are examined.

3.2 Competitive Intelligence

The origins of CI started with Porter (1980) when he studied competitor behaviour and linked the outcome of competitor analysis to competitive strategies. Porter's (1980) study connotes that the CI aids competitive advantage. CI, therefore, arose due to increased global competition and rapid changes that continued to disrupt organisations since the early 1980s as technology and markets evolved (Fleisher, 2004; Nasri, 2011).

For the past decades, there has been an upsurge in CI activities, and most organisations have invested in capabilities and processes to gather and monitor competitor intelligence and be part of the membership of the competitive intelligence association (Calof, Arcos & Sewdass, 2018).

Many organisations have also realised that it has become more misleading and outdated to wait longer before generated data is analysed, and its insights are extremely high risk to the business strategy (Calof, Richards & Santilli, 2017).

Consequently, CI has emerged as a discipline that assists organisations in adapting and flourishing to environmental change in the competitive and complex business environment (Sewdass, 2012; Tahmasebifard & Wright, 2018). Therefore, CI is not information about competitors but is a distinct discipline that can drive and unlock value through the organisation (Gilad, 2016).

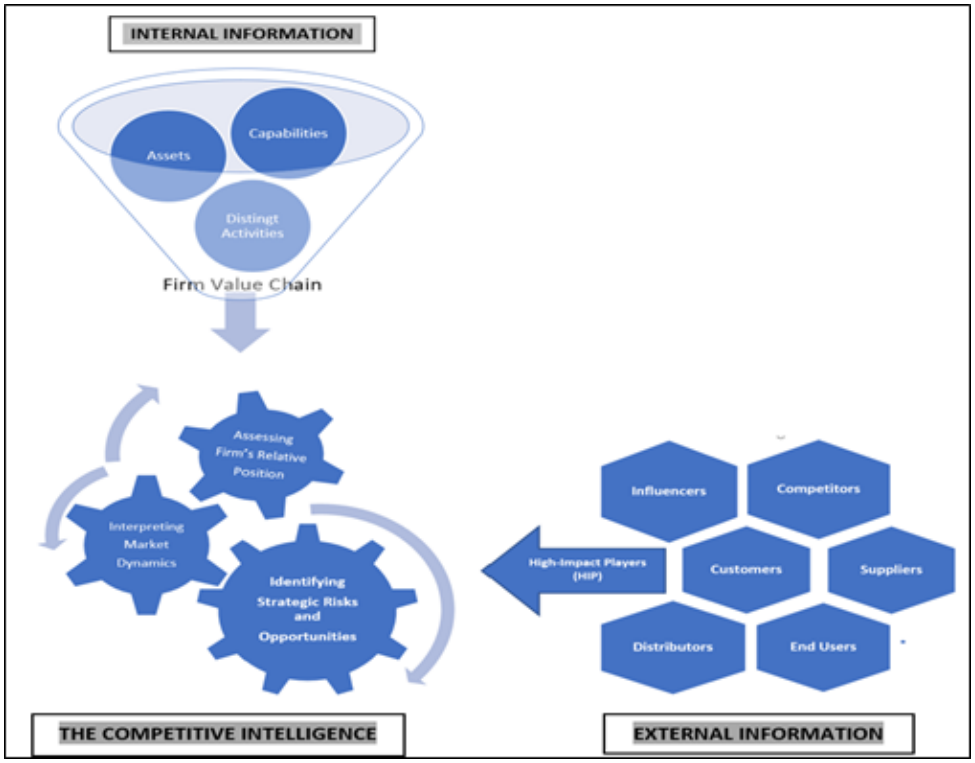
This view denotes that CI pays more attention to the entire value chain of the competitive environment and not just the competition. CI is information about the behaviour of competitors, suppliers, technology, and the business environment (Yap, Rashid & Sapuan, 2013). Gilad (2016) contends that CI should not be confused with information. Information is provided by corporate libraries, research vendors, and web-based programs.

Furthermore, Gilad (2016) stresses that CI enables agility and does not produce information about the present or the future, while technology produces more information within the organisation.

CI comprises competitor intelligence and intelligence collected on customers, suppliers, technologies, and the turbulent business environment. Intelligence, therefore, repositions organisations as markets change to adapt and thrive (Sewdass & Du Toit, 2014).

This view implies that CI provides market insights about the competition rather than competitors and also that CI uses analytics to codify and convert data and information into insights that produce a market dynamics perspective (Gilad, 2016). Furthermore, this view correlates with the model depicted in Figure 3.1 hereunder.

Figure 3.1: The Conversion of Information into Intelligence



Source: (Gilad, 2016, p. 6)

Gilad's (2016) model in Figure 3.1 above shows that data and information are not intelligence. Instead, they serve as input into the CI conversion process. In this process, both data and information are transformed into insights. The CI process, therefore, focuses explicitly on interpreting information and providing decision-makers with differing perspectives of risks and opportunities.

Jourdan, Rainer and Marshall (2008) concur that a structured process allows organisations to transform information into knowledge to survive and thrive in the global economy. Therefore, CI supports organisations in developing and maintaining their competitive advantage (SCIP, 2016). Yet, various definitions of CI have been provided by different authors, and approaches have merged in the field of business. For instance, Søilen (2016) found that CI has been overlaid with definitions in established studies such as decision science and marketing intelligence.

This finding connotes that even if there are various definitions of CI, there is no universal definition for this subject (Pellissier & Nenzhelele, 2013). For example, Liebowitz (2006) defines CI as " the collective added benefits obtained from intangible assets such as employee knowledge, management, stakeholders and customers".

Nienaber and Sewdass (2016) surmise that the definitions of CI should be extended to include workplace-related CI. For that reason, Vriens and Søilen (2014) mention that the scope and definitions of CI should include disruptive intelligence. According to Alnoukari and Hanano (2017), CI is the analytical process that compiles and translates competitor information about their capabilities, performance, and position in the market to develop a competitive strategy for the organisation.

Meanwhile, CI is an ethical and legal process used to gather and analyse competitors' information in their industry to make better decisions to reach strategic outcomes for organisations (SCIP, 2016 cited in Calof et al.,2018). Equally, CI is a legal and ethical practice to collect and analyse data that assist organisations in competing better. (McGonagle, 2016).

According to Du Toit (2015, p.15), CI is:

> "a process or practice that produces and disseminates actionable intelligence by planning, ethically and legally collecting, processing, and analysing information from and about the internal and external or competitive environment to help decision-makers in decision-making and to provide a competitive advantage to the enterprise".

Saravia-Arenasa, Ovallos-Gazabonb and Quintero-Maldonadoc (2016, p.228) define CI as "a structured process by methods that allow organisations to transform information into knowledge for their survival and thrive in the globalised economy".

As a result of this process, organisations gather knowledge about the competition, customers, suppliers, technologies and markets for making decisions (Saravia-Arenasa et al., 2016). Notably, most CI definitions pay more attention to its objectives and processes (Calof, Richards & Smith, 2015).

Štefániková and Masárová (2014) likewise assert that CI is a process of evaluating and monitoring the competitive landscape to enable organisations to make precise decisions amid its competition. However, Gilad (2016) believes that the CI is a process used to make strategic and tactical decisions. It provides intelligent information gathered internally and externally for an organisation to adapt to changing market conditions.

This view implies that the role of CI is to anticipate and facilitate market changes and assist organisations in adapting and adjusting to rapid changes. In so doing, organisations will be on alert regarding competitors' activities and dynamics and develop tactics to respond to market sophistication and demand (Tuan, 2016). CI is, therefore, a process of gathering actionable intelligent information on which executives can make effective strategic decisions about customers, competition, and market opportunities (SCIP, 2014).

McGonagle (2016) also corroborates the above view and posits that CI is actionable intelligence about the entire competitive environment. In addition, McGonagle (2016) upholds that the competitive environment comprises the organisation's competitors, customers, suppliers, and regulatory and political environment.

Thus, sustainable CI processes should plan, collect, analyse, and communicate intelligent information and create awareness for decision-makers to take appropriate action that will ensure the survival of organisations in the present fiercely contested business environment (Saayman, Pienaar, De Pelsmacker, Viviers, Cuyvers & Jegers, 2008). So, CI plays an essential role in tracing and analysing intelligent information for organisations to respond to the external and internal environments (Calof et al., 2015).

In effect, CI assist organisations in obtaining and maintaining their competitive advantage (McGonagle, 2016). CI facilitates strategic planning in an organisation and comprehends the process of defining, gathering, analysing, and dispersing information for decision-making (See for example, Du Plessis & Gulwa, 2016; Gauzelin & Bentz, 2017; Jenster & Søilen, 2013). Bulley, Baku and Allan (2014) draw attention to CI as a continuous integration process incorporating several activities and structures implemented in a sequence (De Pelsmacker et al., 2005). Conversely, McGonagle and Misner-Elias (2016)

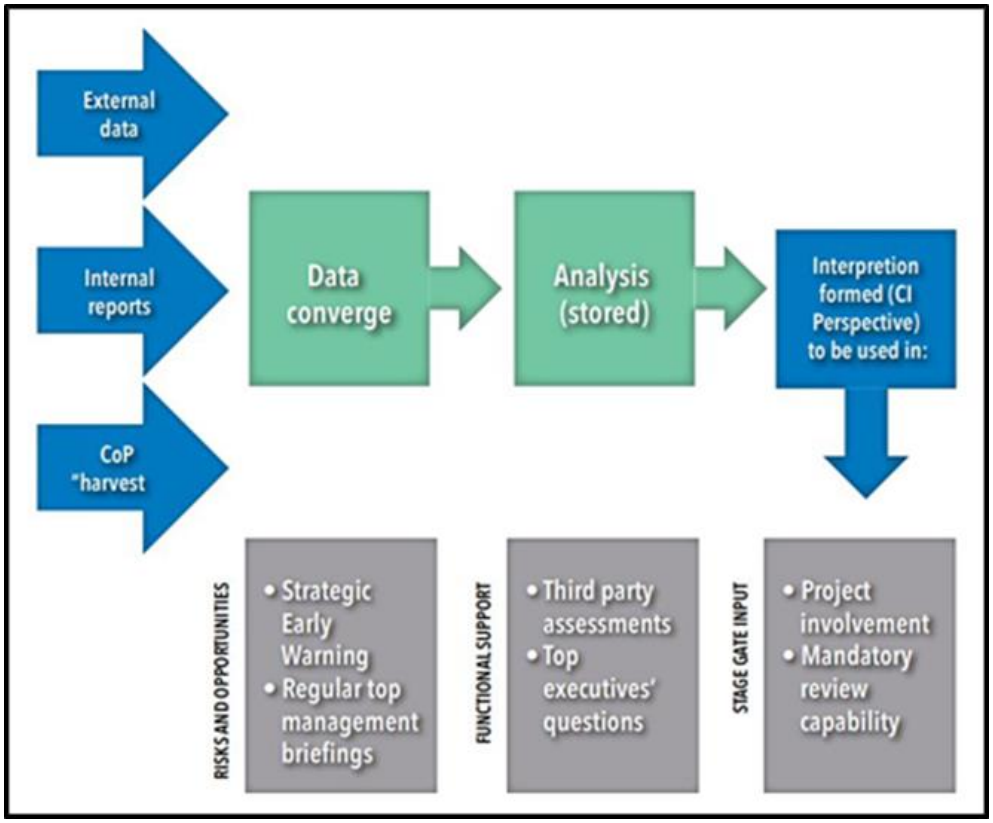
advocate that the CI process develops when executives need intelligence to make informed decisions.

Furthermore, McGonagle and Misner-Elias (2016) contend that CI is a product that is diffused by an analyst instead of a process fused into management. Priporas, Gatsoris and Zacharis (2005) hold that CI is a product when data obtained from the industry's competitors is used to respond and act. Then, CI systematically acquires, analyses and develops data into knowledge for competitive advantage and fast-tracks decision-making process (Priporas et al., 2005).

According to Gilad (2016), there are different steps in a CI process ranging from steps 1 to 7 (Please refer to Figure 3.2 hereunder). In this model, Gilad (2016) upholds that the objective of a CI process is to create competitive insights or a market perspective that reveals possible risks and opportunities.

Consequently, CI manages and reduces risk by strategically analysing intelligent information to enhance the competitiveness of organisations while managing network resilience to claim a distinct competitive advantage over its opponents (Gatsoris, 2012). This opinion highlights the significance of CI in shaping strategic decisions and driving organisational performance (Mohsin, Halim & Ahmad,2015).

Figure 3.2: The Competitive Intelligence Process

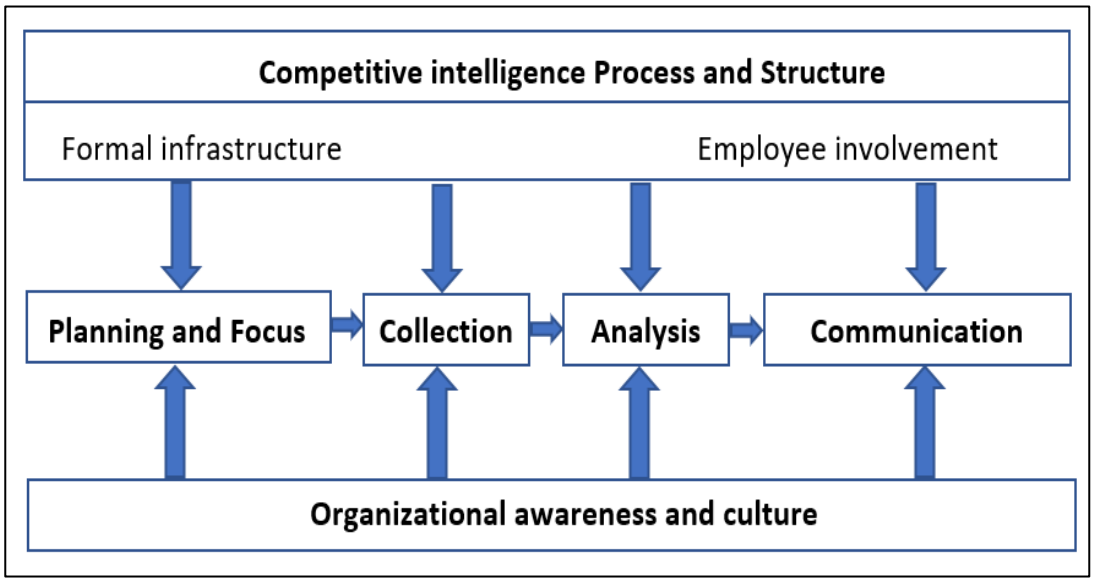


Source: (Gilad, 2016, p.13)

Dishman and Calof's (2008) study found that some CI practices effectively collected information. However, they were ineffective in process capability and performing analysis.

Furthermore, Dishman and Calof (2008) tailored a model that systematically addresses significant factors through various phases of gathering and disseminating intelligent information within the organisation (Figure 3.3). The model in Figure 3.3 hereunder illustrates that CI processes produce desired outcomes when supported by organisational culture, awareness, and structures.

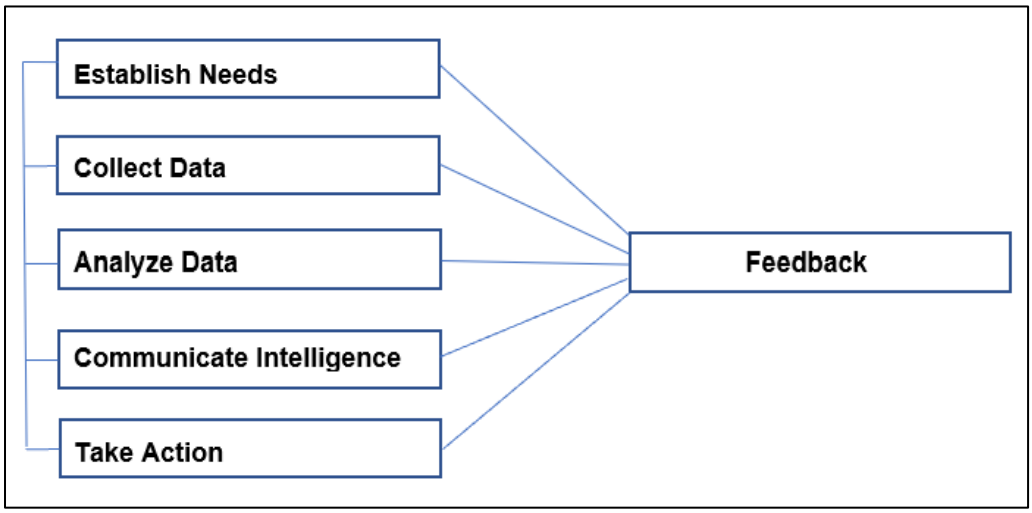
Figure 3.3 Model of Competitive Intelligence



Source: (Dishman and Calof, 2008, p.779)

Similarly, McGonagle and Misner-Elias (2016) maintain that CI processes are derived from the strategic intelligence cycle described in government intelligence literature (See Figure 3.4 hereunder).

Figure 3.4: The Competitive Intelligence Cycle



Source: (McGonagle and Vella, 2003, p.8)

Furthermore, McGonagle and Misner-Elias (2016) stress that CI processes separate the intelligence requester from the intelligence provider in this model. The steps in the CI cycle validate that once needs are established; data is collected and analysed; then, once intelligence is communicated; decision-makers take action. This model shows that all the phases of the CI process are interrelated (Strauss & Du Toit, 2010). The feedback provided at every step of the process is essential to the CI cycle.

The quality output of CI consequent from the organisation's intelligence cycle advances strategic decision-making (Bartes, 2014c). CI identifies appropriate tools and techniques for conducting strategic early warning competition analysis (Gilad, 2016). In essence, the purpose of CI is to answer complex questions and provide intelligence for decision-making along with early identification of potential threats and developing opportunities (McGonagle & Misner-Elias, 2016).

This view indicates that CI is a strategic tool that systematically enables organisations to analyse intelligent information (Amiri et al., 2017). The output of the CI process thus provides forward-looking insights to executives to make sound decisions to adapt and adjust current strategic choices and options to ubiquitous changes in the business landscape (Arrigo, 2016).

Importantly, CI's intelligence helps decision-makers formulate strategies and make precise choices (Mohsin et al., 2015). Moreover, CI creates and adds more value and equips executives to make specific investments and long-term strategic decisions quicker than the competition (Amara, Søilen, Vriens, 2012). CI also stimulates the creativity of new ideas, enhancing organisations' ability to think, plan, predict and inventively solve complex problems in today's unstable global environment (Popovič, Hackney, Coelho & Jaklič, 2012). The objective of CI is, therefore, to support innovation (Salvador & Salinas, 2014 cited in Calof et al., 2015, p.71).

The prevailing literature themes indicate that CI is a strategic analysis-based management tool, not a technical information management activity (Gilad, 2016). This opinion suggests that technology gathers and diffuses information while CI analyses intelligent information and provides competitor insights for effective decisions.

Consequently, CI is an ongoing process that applies psychological techniques and technology to analyse data and information to transform it into intelligence (Fuld, 2010).

CI processes analyse, refine and sieve information to develop intelligence and knowledge (Drucker, 1988; Kahaner, 1996). Therefore, CI is a strategic tool that aids the identification of potential opportunities and threats (Amiri et al., 2017; Du Toit, 2013 cited in Calof et al., 2015, p. 71; Pellissier & Nenzhelele, 2013). These views imply that CI is a management tool that supports strategic planning (McGonagle, 2016).

In essence, CI capabilities enable organisations to predict competitor activities to remain competitive and attain their goals through effective decisions based on an intensive strategic plan to adapt and adjust to the winds of change (Amara et al., 2012). CI practices are, therefore, key to strategic planning, and they have a significant effect on organisational performance (Jenster & Søilen,2013). Thus, CI is linked to strategy formulation because it gathers and processes information (Dishman & Calof, 2008).

In sum, CI precisely transforms valuable information and data into intelligence about customers and the competition. CI provides organisations with actionable intelligence that compares their performance to industry peers and facilitates internal decision-making.

Furthermore, CI goes beyond research and analytics and provides acumen for executives to observe the external environment and monitor key trends that are likely to change the long-term survival of an organisation (Arrigo, 2016).

CI is essential in shaping the organisation's strategy (Gauzelin & Bentz, 2017). This study's conceptual model integrates Competitive Intelligence Embeddedness (CIE) organisational and market factors, information attributes and organisational performance.

This study focuses on CI from drivers that stimulate organisational performance. The following sections explore the causative relationships between CI and strategy management and Sustainable Competitive Advantage (SCA).

3.3 Strategy Management

As organisations tend to work strategically with entrepreneurial processes, they are liable to embrace the winds of change in complex business environments (Höglund, Holmgren Caicedo & Mårtensson, 2018). This view shows that organisations need to rethink their strategies to respond to the changing economic surroundings (Ghemawat, 2010).

Sewdass and Du Toit (2014), however, contend that in today's intensely competitive environment, organisations in developing countries are less dynamic, as they resist change compared to organisations in developed countries. These organisations require strategic information appropriate to support their decision-making processes in their operations (Arcos, 2016).

Therefore, analytical insights and intelligence are, central to strategy formulation and communication (Arcos, 2016). Notably, intelligent information arms organisations with insights from the competitive environment so that decision-makers can respond swiftly to the challenges imposed by the changing conditions (Arcos, 2016).

In tandem, an intelligent function interprets changes and informs management decisions and actions leading to strategic agility (Arcos, 2016). Therefore, strategy is integral to providing direction and setting goals for the organisation. Strategy is the action plan implemented by an organisation to achieve its vision (Foley & Guillemette, 2017).

Strategy formulation, therefore, needs to be consistent, clear and focused (Del Corso, 2015). Consequently, strategic practices are employed to allocate resources appropriately, steer the company in the right direction, and set in processes to monitor and control the organisation's strategic outcomes (Jarzabkowski, 2003). Similarly, Foley and Guillemette (2017) advocate that strategy is a choice made by an organisation to allocate its resources appropriately to attain SCA.

Thus, strategy leads to effective controls, monitoring and execution of the corporate strategy (Del Corso, 2015). For that reason, the strategy should embrace flexibility and responsiveness and provide direction to the pursuit of attaining corporate objectives in turbulent times (Grant & Jordan, 2015).

According to Normann and Ramirez (1993), strategy provides conceptual models and frameworks that guide management to identify opportunities in the competitive environment, create superior customer value, and deliver economic value for the organisation.

Notably, the strategy sets specific actions and goals for the organisation to create and capture value over time to generate positive results (Favaro, 2015). The strategy must go beyond best practices. In so doing, organisations should claim and choose a distinct position in the market and lower costs or better serve a set of customer needs than the competition (Porter & Kramer, 2006).

In effect, an out-ward looking strategy calls for leaders and employees to be proactive and put the customer at the centre of activities in their strategic planning processes to outsmart the competition (Höglund, Holmgren Caicedo & Mårtensson, 2018). This view points to the significance of the strategic planning processes in setting strategic enabling priorities, decisions and growth plans for the organisation (Ashkenas, 2013).

In addition, high-performing organisations have unleashed their strategies' potential by improving their strategic planning processes and execution to realise their gains and remain resilient in the fiercely contested business environment (Mankins & Steele, 2005).

Strategy is, therefore, the link between an organisation's external environment, thriving, execution, and strategy implementation to discern the organisation from its rivals (Grant & Jordan, 2015). Additionally, Grant and Jordan (2015) maintain that strategy provides a common purpose in tandem with committing resources while creating value.

Johnson, Whittington, Scholes, Angwin and Renger (2016) proclaim that strategies are the keys to the future survival of organisations. Furthermore, Johnson et al. (2016) uphold that organisations should develop their strategy to analyse their operational environment and craft their strategic plans. As a result, Johnson et al. (2016) divided strategy development into deliberate and emergent strategies. Deliberate strategy refers to the formal planning intended to assist organisations in realising expected outcomes (Johnson et al., 2016). Also, deliberate strategies give organisations a sense of purposeful direction

(Mintzberg, 1994). This view signifies deliberate strategies focusing on specified goals and objectives.

Conversely, emergent strategies use processes identified by organisations and assessments of unexpected outcomes to formulate new plans and strategies to ensure the sustainability of organisations in the long run (Johnson et al., 2016). The emergent strategy is an unplanned strategy that responds to unexpected opportunities and challenges (Stretton, 2017).

Mintzberg (1994) maintains that an emergent strategy is a pattern of action that develops over time within the organisation apart from its clear missions and goals. Furthermore, Mintzberg (1994) proclaims that an emergent strategy is a set of actions or behaviours consistent over time to identify new patterns that shape the original strategic plan to achieve a different outcome.

This opinion shows that emergent strategies infuse innovation into the planning process. The convergence of deliberate and emergent strategies will then guide and inspire learning within the organisations.

Meanwhile, organisations may well pursue umbrella strategies, and tailor broad outlines that are more deliberate while allowing the details to emerge as the organisation evolves (Mintzberg, 1994; Hax & Majluf, 1996). For that reason, Johnson et al. (2016) have also created a model that explains the blend between deliberate and emergent strategies leads to a realised strategy (See Figure 3.5 hereunder).

Realised strategies are a product of what the organisation plans to do regarding what will be pursued by the organisation over time (Stretton, 2017). Simply put, a realised strategy is a strategy that organisations follow.

Figure 3.5 Deliberate and Emergent Strategy Development

Source: (Johnson et al., 2016, p.403)

In retrospect, Fahey (2007) believes that strategy is about creating and realizing new market opportunities that add, create, and deliver customer value. Therefore, strategy making is essential for executives and managers to find intelligence information relevant to strategy development and execution throughout the organisation (Fahey, 2007).

According to Favaro (2015), strategy and implementation are inseparable, suggesting that they are independent, and their execution occurs simultaneously and not in a sequence. Furthermore, Favaro (2015) illustrates that tangible activities, decisions, and outcomes are the basis for successful strategy implementation. This view connotes that competition occurs at the business unit level (Porter, 1988).

Del Corso (2015) has discovered a synergy between corporate strategy and implementation and execution at an operational level. Therefore, strategy implementation and execution are key success factors that assist organisations in translating their strategic choices into tangible outcomes (Favaro, 2015). According to Kavale (2012, p. 59), strategy formulation and evaluation are followed by strategy implementation and feedback.

Information should thus easily flow across organisational boundaries to execute corporate strategy (Nielson, Martin & Powers, 2008). If intelligent information flows, it will improve organisational agility (Gilad, 2016).

Likewise, Neilson et al. (2008) found that when decisions are clarified, and information is disseminated throughout different levels in the organisation, the correct structure will follow strategy, accelerating the speed of execution. Consistent with these views, Chandler (1962) has identified that a long-term coordinated plan was required to offer a corporation structure, direction, and focus.

A study by Kavale (2012) concluded that structure and strategy are closely related and also recommended that during the foundation of crafting and formulating strategy, leadership involvement should be a prerequisite, and this will attest to the alignment of the required structure that will support the execution and implementation of the organisation's strategy. Integrating strategy with organisational activities and structures is key to realising sustainable strategic advantage (Porter, 2008).

Porter (2008) asserts that competitor activities and the organisation's resources construct organisational structures. This view implies that organisations are more promising to deliver superior performance if there is a close alignment between strategy and structure (Kavale, 2012).

An organisation's strategy must be aligned to the isolated operating business environment. While an organisation will adapt to the forces of change to prosper in the dynamic and intricate business environment (Kavale, 2012).

Thus, an organisation will also attain a Sustainable Competitive Advantage (SCA) if its strategy is aligned with its internal core competencies. If the organisation's strategy matches its internal competencies, it will acquire market share and deliver superior results among its industry peers (Maune, 2014a).

So, the organisation's strategy must be acceptable to the wider competitive environment to create economic value through its distinctive competencies to maintain its dominant position in a fiercely contested market (Werther & Chandler, 2006).

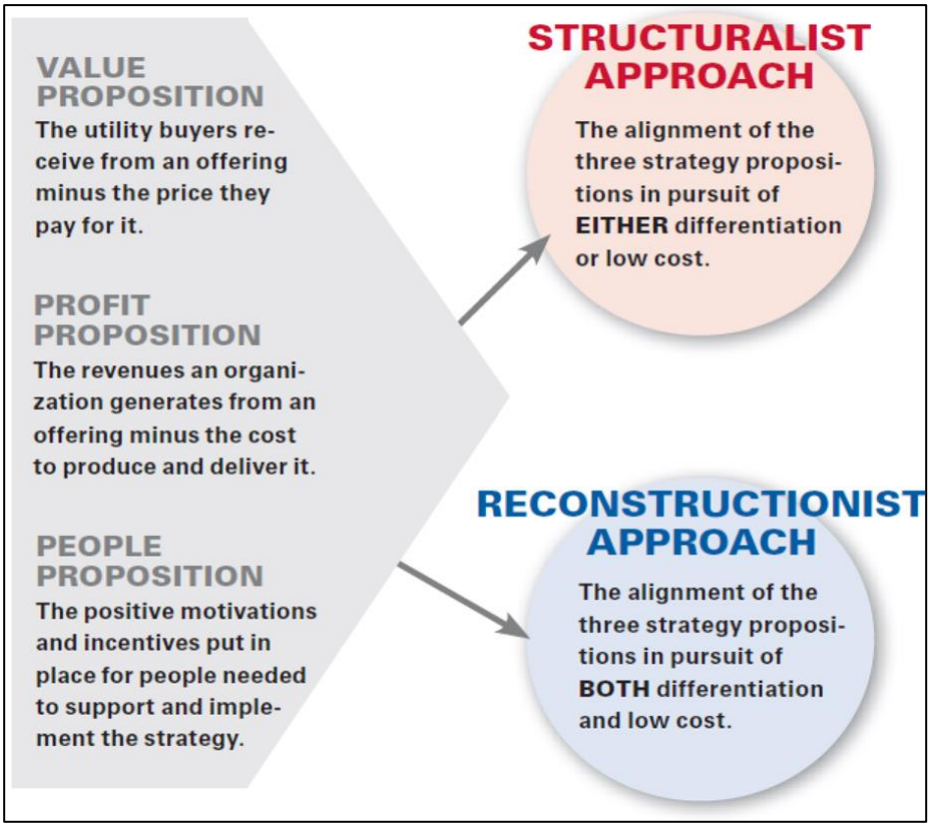
According to Johnson (2016), structure and strategy are so inseparable, thus suggesting that the degree of dependency on each other cannot be overlooked. Strategic options are therefore constrained by the environment whereby strategies shape industry structures (Kim & Mauborgne, 2009).

In addition, Kim and Mauborgne (2009) advocate that strategic alignment empowers an organisation to recreate its environment. Moreover, Kim and Mauborgne (2009) point out that aligning and developing the organisation's value, profit, and people propositions stimulate strategy implementation.

This strategic alignment highlights the significance of the three strategic propositions to organisational activities (See Figure 3.6 below). The output of these activities allows strategy to shape the structure, and this alignment leads to strategy implementation (Kim & Mauborgne, 2009). Noticeably, a mismatch between strategy and structure usually leads to inefficiencies, underperformance, and a lack of strategy execution and implementation (Kavale, 2012).

This means that organisational alignment between its structure and strategy is essential for the strategic management process (Kavale, 2012). This connection between structure and strategy is depicted in Figure 3.7 below.

Figure 3.6 Achieving Strategy Alignment

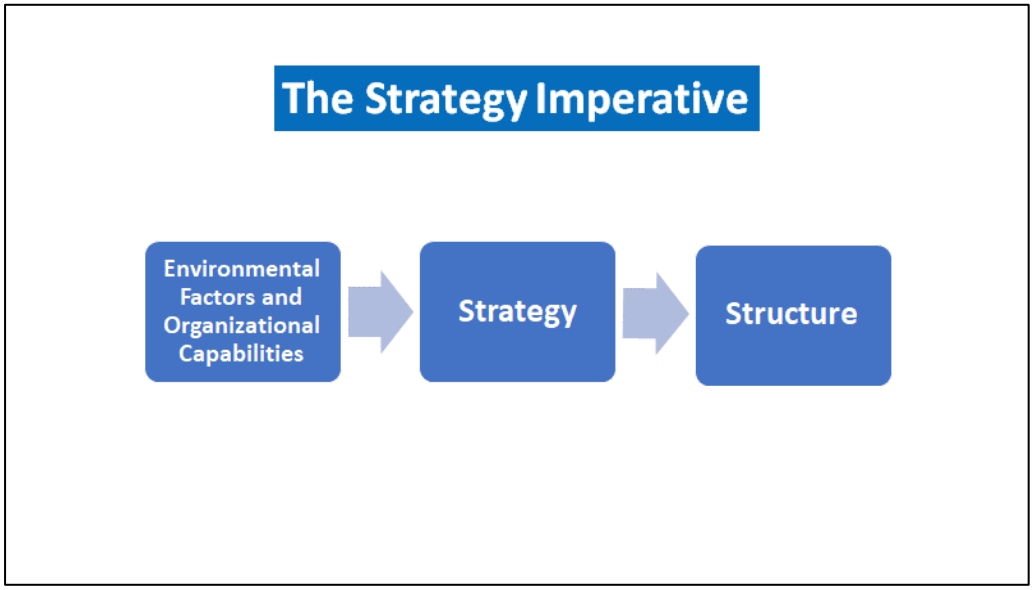


Source: (Kim and Mauborgne, 2009, p.76)

In Figure 3.7, Johnson, Scholes and Whittington (2008) demonstrate that environmental factors and organisational capabilities significantly affect strategy formulation and the adequate structure to support strategy and implementation. CI provides key information about the competitive business environment during strategy formulation and decision-making (Gračanin et al., 2015).

Specifically, the organisation's capabilities to configure its resources with opportunities in the external environment validate its strategic alignment with the external environment and structure. In so doing, an organisation will achieve greater economic value in the turbulent business environment (Johnson, 2016). The organisational structure, therefore, comprises capabilities, culture, people, processes, and technology.

Figure 3.7 Strategy Structure Fit



Source: (Johnson et al., 2008)

The structure is fully integrated with the strategy to ensure that the organisation attains its mission and goals (Kavale, 2012). At the highest level, strategy development is shaped by the norms of appropriate strategic choice and scale as well as the organisational structure (Maritz & du Toit, 2018). According to Calof and Wright (2008), at the highest level, CI integrates the knowledge of everyone in the organisation.

In that way, CI scans the environment and collects intelligent information relevant to strategy development and execution to inform actionable strategies (Fahey, 2007). CI scans the environment to align the organisation's strategy with the environment. In this manner, CI plays a vital role in the strategic decision-making process (Dishman & Calof, 2008).

For the intelligent function to produce strategic insights, CI performs environmental scanning and analyses the market to anticipate intrinsic changes to influence the organisation's current and potential strategies in its operational environment. In so doing, it provides leaders with strategic focus (Fahey, 2007). Consequently, CI identifies market opportunities and risks to provide organisations with an advantage to adapt, adjust and

change their strategic choices and options early enough to respond to the external environment (Gilad, 2015c).

Furthermore, Gilad (2016) states that organisations are agile when they adapt their strategies to the changing and emerging trends in the market. In addition, Gilad (2015c) advocates that CI leads to strategic agility, and its actual value is realised when it aids strategic change.

The organisation's capability to implement its strategy quicker than the competition proves its efficiency and agility regarding the flow of CI throughout the organisation (Gilad, 2016). This points toward the ability of CI to encourage strategic thinking and stimulate dialogue with decision-makers (Gilad, 2016); therefore, organised CI plays a critical role in corporate strategy (Colakoglu, 2011). Previous research from Yap et al. (2013a) indicated that CI is central to supporting strategic decision-making and planning along with identifying opportunities and threats.

Therefore, CI performs competitor analysis, providing insights about opportunities and threats earlier to support executives with strategic planning and implementation (Maune, 2014b). CI also continuously arms organisations with competitive market trends insights so that decision-makers can translate their internal competencies into competitive strategies (Fleisher & Bensoussan, 2015). In essence, CI contributes to strategy development and corporate strategy (Jaworski & Wee, 1992; Calof & Wright, 2008).

CI also equips organisations with competitive strategies, providing intelligent information on which executives can make strategic decisions(Maune, 2014a). Consequently, CI supports organisations with strategic business insights, identifying risks and opportunities with corrective actions required to produce desired results (Bose, 2008).

According to Saayman et al. (2008), CI capabilities advance business development and strategic planning. CI is then central to strategic planning and management processes, as it assimilates data and information from the competitive environment for executives to predict future market trends and opportunities to dominate and control markets (Bose, 2008).

CI analyses and monitors trends in the competitive environment for executives to make relevant strategic decisions (Degerstedt, 2015a). Essentially, CI is the connection between strategic management processes and actions that executives take once they fully grasp the competitive environment (Gračanin et al., 2015). For that reason, CI is a strategic management tool that improves an organisation's competitiveness (De Pelsmacker et al., 2005; Iyamu & Moloi, 2013; Sewdass & Du Toit, 2014).

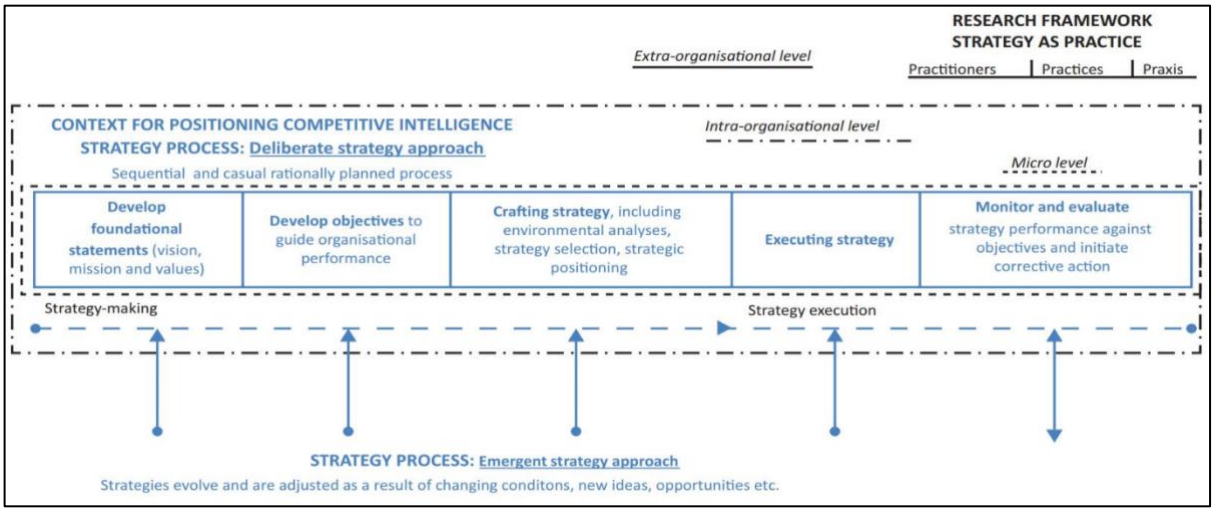
Organisations will thus reap the benefits of the value created by CI through greater awareness and a culture of competitiveness (Maune, 2014a). Similarly, Saayman et al. (2008) advocate that CI is a strategic management tool that adds strategic value and should provide wide-ranging support to business operations. This view indicates that CI activities aid all organisational functions (Adidam, Banerjee & Shukla, 2012).

Thus, organisations use CI to enhance and support their strategic goals and objectives (Iyamu & Moloi, 2013). CI has become a desired strategic tool that provides intelligent information for tactical and strategic decision-making in the current dynamic business environment (Gračanin et al., 2015).

It is evident from the preceding literature themes that the research focuses on strategic management has evolved from purely focusing on strategic processes to strategy as a practice (Jarzabkowski, 2003; Johnson et al., 2008; Langley, 2007).

The literature highlights that strategy as a practice is inseparable from strategic processes (Johnson et al., 2008; Langley, 2007). Essentially, CI overlaps with strategic management processes and practices (Maritz & Du Toit, 2018). For that reason, Maritz and Du Toit (2018) have developed a conceptual model that links CI with strategy processes and practice (See Figure 3.8 below).

Figure 3.8: Strategy Process, Strategy as a Practice and CI



Source: (Maritz and Du Toit, 2018, p.5)

The model in Figure 3.8 above shows that CI integrates with strategy; therefore, the strategy process provides a contextual structure that positions CI within this model (Thompson, Strickland & Gamble, 2015). This model demonstrates that organisations that match their strategy-making process to competitive environments outperform their rivals (Reeves, Love & Tillmanns, 2012).

Equally, this model reveals that the strategy process reinforces deliberate strategy to ensure successful formulation and implementation. Moreover, the strategy process supports an emergent strategy approach where strategies evolve outside of a formal process (Maritz & du Toit, 2018). The deliberate strategy thus employs CI systematically (See Figure 3.8 above).

On the other hand, strategy as practice focuses more on micro-organisational practices where CI monitors and evaluates the organisation's strategy and provides insights for taking corrective action to respond to the competition (Maritz & du Toit, 2018). A well-designed CI system thereby monitors and identifies risks and opportunities attributed to the competitive environment and tailors effective strategic planning processes for the organisation (Stefanikova, Rypakova & Moravcikova, 2015).

In sum, CI integrates strategic processes and practice within different levels of the organisation (Maritz & du Toit, 2018). In that way, CI embraces different organisational structures and further facilitates the inclusion of all managers in strategy to ensure the implementation of strategic decisions (Davis, Jansen Van Rensburg & Venter, 2016; Jansen Van Rensburg, Davis & Venter, 2014).

CI is vital for strategic practice and aids both the deliberate and emergent planning processes in organisations (Maritz & du Toit, 2018). Moreover, CI provides rational planning to the strategy process. Integration of strategic practices and processes fast-track strategic alignment, ensuring the organisation's strategic priorities are responsive to the ecosystem (Walter, Kellermanns, Floyd, Veiga & Matherne, 2013).

This view shows the integration of CI and strategy implementation yields a competitive advantage (Colakoglu, 2011). CI thereby constructs strategic profiles of an organisation's competition to provide insights for executives to take probable actions and strategic trade-offs to manage network resilience to capture, create, and extract economic value compared to the competition (Thompson et al., 2015).

In this manner, CI brings together intelligent information and knowledge for decision-making and strategy planning (Maune, 2014a). CI also directs research and development by assisting organisations in identifying potential opportunities for investing in new technology and product development (Iyamu & Moloi, 2013), thus making CI practices imperative in strategic management both in practice and research (Adidam et al., 2012).

For that reason, CI is a business tool that aids organisations with strategic management plans to improve knowledge and communication to stimulate organisational performance (Hussein, Farzaneh & Farham, 2011).

The following section explores the causative relationship between CI and strategy.

3.4 Competitive Intelligence and Strategy Management

Of late, the business environment has been unpredictable and susceptible. As such, organisations are bound to utilise intelligence consequential from the milieus to make operational and technical decisions (Shujahat, Hussain, Javed, Malik, Thurasamy & Ali, 2017).

Meanwhile, companies with correctly organised intelligence will reap the rewards of gaining true value derived from the outputs of disruptive innovation and sustainable competitive strategies to lead markets (Bartes, 2014c). This signifies that an effective strategic management process integrates analysis and intuition in decision-making. Indeed, this will ensure that data and information about competitor activities and emerging trends are gathered and analysed to attain organisations' goals (Kahaner, 1996).

According to Mohsin et al. (2015), intelligence is a product of knowledge and experience. Intelligence is obtained from customers, employees, management and stakeholders (Liebowitz, 2006). Calof, Arcos and Sewdass (2018) maintain that intelligence is part of the foresight process and plays a significant support role.

Knowledge Management (KM) and CI play a vital role in strategic management processes (Shujahat et al., 2017). Notably, organisations with effective KM and CI systems are armed to gain knowledge and intelligence that shapes the internal and external environments (Shujahat et al., 2017). The organisation then acquires knowledge and intelligence to analyse and make strategic decisions during turbulent times (Ghannay & Zeineb,2012).

As globalisation and technology have transformed the world economies, the ubiquity of knowledge and the pace of innovation are accelerating (Barber, Donnelly, Rizvi, Summers, 2013). With these events occurring, global competitiveness advances in intensity and sophistication, thus affecting organisations' capabilities to obtain relevant information (Zenaide & Thomé e Castro, 2015). Essentially, data needed to create corporate strategies is sourced from competitor activities and their strengths relative to their interests in the market (Bartes, 2014c).

Notably, the global economy is suffering and experiencing the worst crisis ever (Barber et al., 2013). Bartes (2014b) upholds that the quality and significance of data for strategic decision-making by top management grows significantly in periods of economic depression.

Seemingly, present systems cannot create relevant data for top management to make quick strategic decisions in the current and highly demanding market environment (Bartes, 2014b). In contrast, Fleisher and Bensoussan (2015) believe that some effective tools and techniques, such as aggregation methods and technology used to analyse data sources. These tools offer business intelligence about nascent market opportunities for organisations to gain a competitive advantage. Companies constantly struggle to provide decision-makers with the appropriate intelligence on time (Du Toit & Begg, 2007).

Meanwhile, BI is an analytical tool that transforms external and internal data into knowledge that supports organisation decision-making processes. BI also plays an essential role in strategic management and corporate strategy (Alnoukari & Hanano,2017). BI is a competitive differentiator because it combines operational data with analytical tools to provide decision-makers with competitive information (Brinkmann, 2015).

CI is a subset of BI; hence, these concepts are used interchangeably depending on the decision-making level. For instance, CI is used for strategic decisions, while BI is used for tactical decisions (Köseoglu, Ross & Okumus, 2016). Yet, another view suggests that when CI is used for strategic decisions, it is ranked very high in making capacity expansion decisions amongst all the other items investigated (Ching & Zabid, 2017).

Işik, Jones and Sidorova (2013) suggest that decision-makers influence the extent to which business intelligence supports flexibility and risk in decision making, thus indicating that strategic decisions are based on credible and relevant information. A CI system objective, therefore, aims to aid companies in claiming and creating value through distinctive competencies by overlapping potential boundaries to manage network resilience and eliminate entrepreneurial rivals in the business environment (West, Ford & Ibrahim, 2015).

To remain competitive in business today, leaders must also take proactive measures and formulate competitive strategies for organisations before related events occur. In doing so, leaders should be in touch with competitor activities and acquire usable strategic knowledge about competitor capabilities, intentions, position, and performance in the marketplace to enter new markets and claim a distinct marketplace. This view implies that executives should acquire intelligent information that aligns with the organisation's strategic objectives and corporate development strategies (Bartes, 2014c).

Meanwhile, leaders often fail to comprehend the complexity of what change involves to acclimate to the changing business environment characterised by complex decision-making and the requirement for speedy response and action in the face of extensive, unexpected changes caused by unfavourable market conditions (Stanford, 2016).

Consequently, faster information processing and knowledge growth appropriately respond to a radically changing environment. Yet, executives are effectively dazed with information lacking the intelligence to aid quicker strategic decisions (Sewdass & Du Toit, 2014). These executives still need to be reminded that grasping, choosing, and implementing a strategy does not occur in a competitive vacuum (Barney & Zajac, 1994).

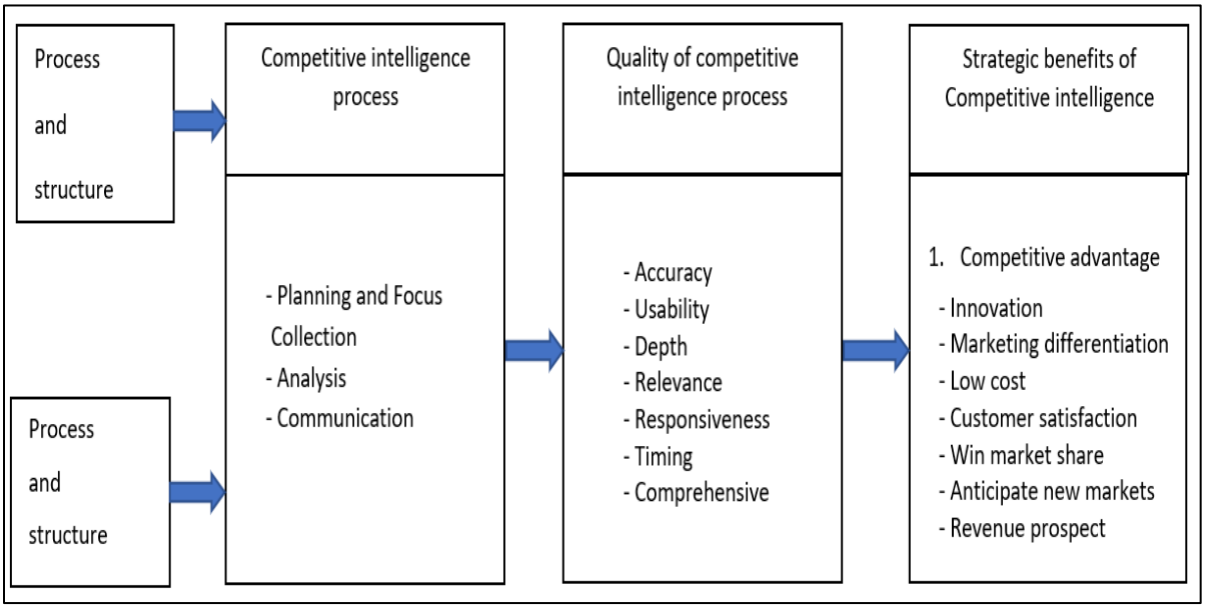
Köseoglu et al. (2016) showed that managers only use CI for planned activities instead of strategic resolutions. Furthermore, the authors found that CI activities, strategic planning, and competitive position had no direct correlation since most managers had been trained on tactics to gather competitor intelligence. In contrast, Ching and Zabid (2017) found that managers only used CI for strategic decision-making from sources of information such as customers, competitors, newspapers and periodicals.

For that reason, Al-Zu'bi's (2016) study recommended that managers should be conversant and know how to evaluate and identify organisational agility to accomplish organisational goals. Furthermore, his study showed that all the strategic intelligence dimensions impacted organisational agility and more dimensional creativity. Leaders should be in touch with competitors' competencies, intentions, strengths, and strategic plans.

In this context, CI analyses competitor abilities, intentions, and susceptibilities preparing organisations to proactively cope and deal with market development (Uzoamaka, Aningbogu & Chidmma 2017a). For an organisation to remain agile, adapt and adjust its strategic goals in a dynamic and evolving context, CI will fulfil an intelligence function that anticipates and provides insights about market developments more rapidly than the competition. Additionally, it will fast-track management decisions and strategic actions (Arcos, 2016).

Nasri (2012) theoretically explored how CI processes influence strategic benefits expansion in an organisation. Furthermore, Nasri (2012) developed a conceptual model for the strategic benefits of CI processes (See Fig 3.9 below).

Figure 3.9: Conceptual Model for Strategic Benefits of CI Process



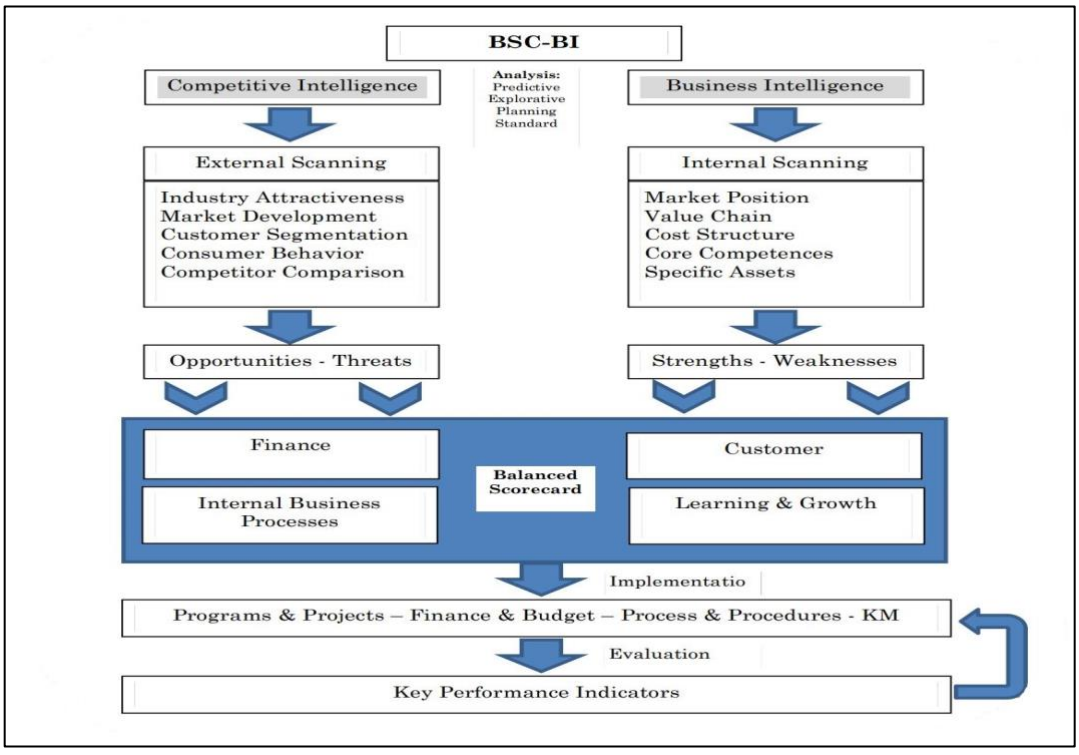
Source: (Nasri, 2012, p. 31)

In this model, Nasri (2012) states that the strategic benefits of CI yield to competitive advantage. This model advocates that CI activities result from the output collected from BI and strategic analysis (Bartes, 2014c).

So, BI is essential in strategy development and improving organisational outcomes to gain strategic capabilities (Brinkmann, 2015). BI and the Balanced Score Card (BSC) are crucial tools for building CI (Olszak, 2014).

First, a BSC is a management tool that assists leaders in articulating their strategy into actionable initiatives and projects (Alnoukari & Hanano, 2017). While a BSC provides a framework for management to implement, execute, monitor and evaluate the organisation's strategy (Olszak, 2014). Alnoukari and Hanano (2017) designed a BSC-BI framework that uses BI and CI capabilities to develop a corporate strategy (See Figure 3.10 hereunder).

Figure 3.10: BSC-BI Framework



Source: (Alnoukari and Hanano, 2017, p. 11)

Alnoukari and Hanano (2017) maintain that this framework integrates BI technologies into the strategy development process. Therefore, BI directly affects corporate strategy and

provides adequate tools and technology to senior management. This view indicates that BI directly affects corporate strategy (Alnoukari & Hanano, 2017).

Meanwhile, BI and CI are integrated to formulate corporate strategies and policies, while BI technology is used effectively to attain organisational results and performance (Alnoukari & Hanano, 2017). BI and CI integrate effectively, adapt and adjust to changes in market positions and the organisation's strategy (Brinkmann, 2015).

According to Uzoamaka et al. (2017a), CI applies modern information technology intensively to answer current needs and strategic decisions for organisations. CI analyses competitive dynamics and identifies emerging opportunities to avoid shocks on time (Uzoamaka et al., 2017a). This means that CI has become a strategic necessity that equips executives with knowledge and information to make strategic decisions (Ahmed, Ahmad, Khoso, Arif & Palwishah, 2014).

As a strategic asset, CI appraises the competitive business environment in quest of taking advantage of opportunities to ensure that organisations gain advantage and cope with challenges and crises (Sun, 2015). Furthermore, Sun (2015) stresses that the efficiency of CI in organisations should be linked to its strategic goals. As a result, the capacity to make a forward-looking judgement is the major output of CI, and it is fundamental to the strategic planning and management process (Bose, 2008). CI supports strategic management and safeguards organisations from laggards in a highly demanding competitive environment (Bartes, 2014c).

Recent research by Uzoamaka et al. (2017a) showed that CI significantly positively influenced market share. In essence, CI creates market opportunities and provides accurate information about competitive environments for organisations to outsmart their rivals (Luu, 2014). This advocate that CI is a proactive technique that analyses and monitors organisations' competitive environments and uses knowledge and intelligence to develop effective strategies (Ahmed et al., 2014). So, the strategic benefits for CI in organisations are innovation, entrance into new markets and revenue growth (Nasri, 2012).

CI largely arms leaders with strategic intelligence to assess competitors' strategies and formulate strategies to counter the competition (Ahmed et al., 2014). Consequently, strategic intelligence is used as an early warning for management to manage risks in the external environment (Campos, Rubio & Quintero, 2014).

CI is a strategic management tool that resides within organisations' spheres of strategic decision-making (Viviers, Saayman & Muller, 2005). In essence, CI plays a significant role in management and strategic management (Zangoueinezhad & Moshabaki, 2009).

Bartes (2014c) similarly states that the greatest value of corporate CI resides within the domains of strategic management. Furthermore, he reiterates that CI needs to be used primarily to solve organisations' strategic challenges and problems. Equally, Bartes (2014b) posits that CI exists in the strategic planning process to analyse intelligent information and provide early discovery of potential challenges and threats that will change the future destiny of organisations.

In contrast, Rapp, Agnihotri, Baker and Andzulis (2015) contend that CI is mainly used to make strategic decisions at different levels of the organisation. It is then critical to have executive sponsors at different levels of organisations who will prioritise competitor intelligence gathered by CI and implement its results to adjust and change the strategic direction of organisations (Calof et al., 2017a). This view signifies a symbiotic relationship between CI and corporate strategy.

CI in organisations resides within the domains of the strategic planning process; besides, its function to assess the internal and external environment is core to strategic formulation (Bartes, 2014a). Although they use CI to cover a range of decision-making areas, academics and strategists use it because of its significance in the strategic management process (Calof & Wright, 2008).

The main focus of CI is to solve strategic issues within and outside an organisation (Bartes, 2014b). CI is commonly used in developing and executing corporate strategy (McGonagle, 2016). CI additionally interrogates strategy as it asks how the environment will affect its sustainability. In tandem, foresight is forward-looking and tends to focus

more outside the organisational frame with a longer-term view of the future (Calof et al., 2015).

Bernhardt (1996) agrees that CI challenges reinforce the organisation's vision and strategy. Calof et al. (2015) point out that CI assists organisations in adapting their strategies to the current environmental context in the short to medium term. The authors further advocate that CI uses prognostic to study and analyse prospective markets; thus, it provides direction for executives to make informed strategic decisions.

CI forecasts the future, contributing vastly to strategic planning (See Bartes, 2014a; Calof et al.,2015; Tanascovici & Hagiu,2013). Therefore, KM and CI apply alternative strategies to solve potential problems. This highlights the synergistic relationships between KM and CI in the strategic management process (Shujahat et al., 2017).

In a study that demonstrated knowledge and information management as instruments to develop technological foresight, Canongia, Antunes and Pereira (2004) applied CI tools to identify international trends and develop the technology's foresight. This study implies that foresight supports CI in related fields of research (Hammound & Nash, 2014). For this reason, CI and foresight pursue the future by scanning the environment for potential challenges and opportunities (Calof & Smith, 2010; Hammond & Nash, 2014).

In essence, CI aims to equip management with the foresight and insight to make strategic decisions (Bernhardt, 1996). Both CI and foresight are futuristic and analyse the environment to detect and prevent any strategic surprises (Calof et al., 2018). CI can analyse intelligent information and recognise looming potential challenges that will change the future earlier than later (Bartes, 2014a).

This points toward the similarities between corporate foresight and competitive intelligence (Calof & Smith, 2010; Calof et al.,2015; Hammond & Nash, 2014; Canongia et al., 2004). CI, therefore, supports strategic planning and predicts potential challenges and opportunities in the external environment even though it provides solutions to them (Bartes, 2014c; Calof et al.,2015; Hagiu & Tanascovici, 2013).

In contrast, Bartes' (2014b) research highlighted that CI's role was wider than obtaining information relevant to organisations' strategic decisions. Furthermore, Bartes' (2014b) study further showed that CI's true value comes from its accurate analysis and evaluation of information that provides senior management with a competitive advantage in the market. As a result, CI is a high-value activity that precedes company growth, market research, and strategy planning.

Essentially, CI supports creating and implementing a winning competitive strategy (Bernhardt, 1996); and Calof and Wright's (2008) findings indicated that CI supports strategic decision-making relating to corporate or business strategy, business development, research, and development.

Consequently, CI impacts a wide range of decision-making and is vital to formulating and developing business strategy (Bartes, 2014c; Calof & Wright, 2008). According to Arcos (2016), the success of strategy formulation depends on communication; thus, communicating business strategies requires analytic inputs about the organisation's operational environment and stakeholders. This opinion shows that correctly organised intelligence signifies CI and strategy management synergies.

However, Reeves et al. (2012) found that successful strategy formulation depends on the flexibility and probability of changing the competitive business environment and the organisation's ability to change the ecosystem. CI can assist with strategy formulation by understanding the organisation within itself, its industry, and its competitors (Ranjit, 2008 cited in Ebere, Chri–Nnamchi & Victoria, 2017, p.30).

Bartes (2014c) contends that CI's actual outputs mostly applied to operational rather than strategic management, even though top management always needed credible data to predict the future when making strategic decisions. He later found CI linked to strategic management and a system application discipline in an environment dominated by disruptive innovation (Bartes, 2014c). Furthermore, Bartes (2014c) maintains that CI is part of the strategic planning process, primarily intended to collect relevant data, analyse information and the prospective challenges that separate market leaders from followers.

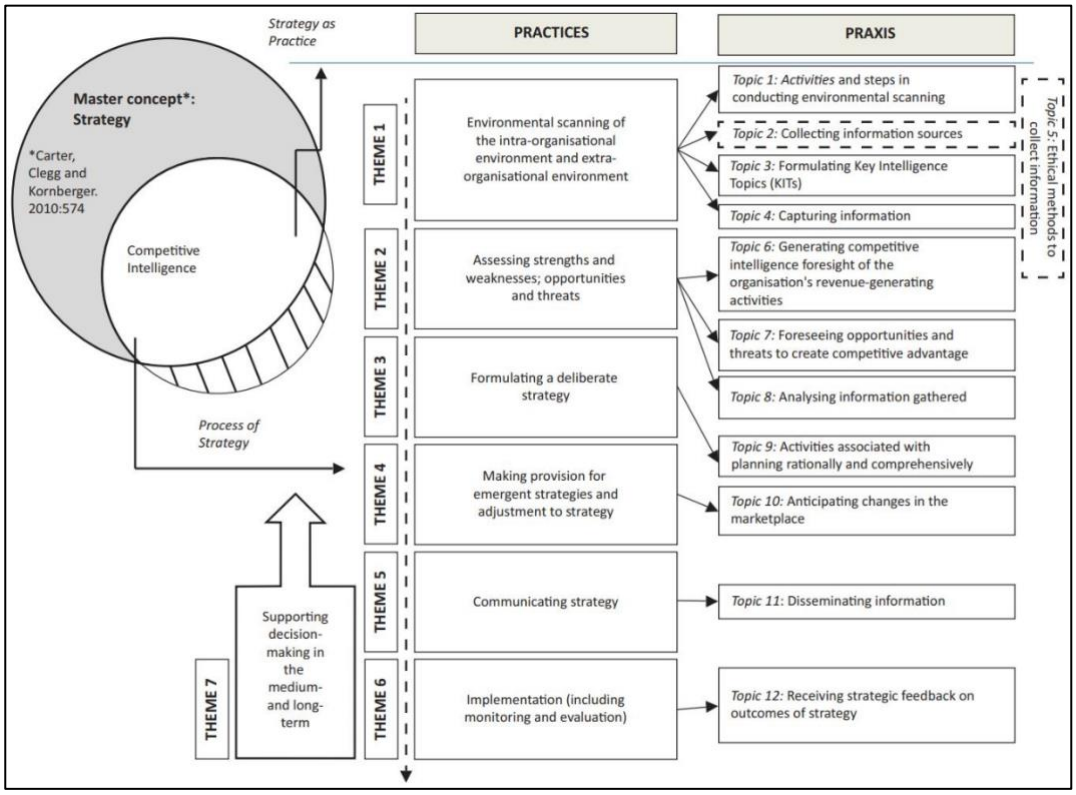
Concurring, Franco, Magrinho and Ramos Silva (2011) posit that CI is a strategic management information tool that allows decision-makers to outstrip market trends and competitors. Moreover, Franco et al. (2011) state that CI assists organisations with identifying and assessing threats and opportunities in the business environment and determining the actions or reactions most suited to the developmental strategy of the organisation.

Consequently, CI identifies areas of improvement in tandem with risk opportunities, which is core to strategic business analysis (Ebere et al., 2017). CI is entrenched in extra and intra-organisational practices and plays a significant role in the practice turn strategy (Maritz & du Toit,2018). The integration of CI and strategy is vital in the strategic decision-making process. CI and strategy management practices thus translate strategic plans into sustainable organisational performance (Adidam et al., 2012).

The above view signifies that CI performs a separate function in an organisation even if it shares similar traits with strategy—in particular—strategy formulation (Maritz & du Toit, 2018). CI consequently supports strategic decision-making processes in response to the competition, and it addresses customers' needs and perceptions (Stefanikova et al., 2015).

Carpenter and Sanders (2013) further hold that CI activities and practices are prearranged to adapt to the different phases in the strategic management process, mostly in the formulation and implementation stages. However, Maritz and Du Toit (2018) observed that CI activities were mainly linked to strategic decision-making rather than management processes. They have also proposed a conceptual framework that integrates CI with strategy practices (See Figure 3.11 hereunder).

Figure 3.11: Integration of Strategy and Competitive Intelligence



Source: (Maritz and Du Toit, 2018, p.11)

Furthermore, Maritz and Du Toit (2018) link seven literature themes to twelve different topics in this conceptual framework. Their framework indicates an overlying area between CI and strategy (Please refer to Figure 3.11 above). CI thereby assists in the contribution of the strategic plan and process. This view indicates that CI is essential for integrating all strategic practices, suggesting the existence of causative relationships between CI and strategy processes (Maritz & du Toit, 2018).

Inevitably, CI activities are linked to the planning and strategic planning process. Additionally, CI contributes to the organisation's strategy while verifying the effectiveness of strategic decisions (Maritz & du Toit, 2018). Grant and Jordan (2015) posit that the strategic planning process is progressive. It includes creating the vision and objectives and selecting the strategy, while CI practices are used to determine strategic outcomes and priorities (Maritz & du Toit, 2018).

CI is central to shaping the strategic direction within organisations. Maritz and Du Toit (2018) also found that CI does not overlap with strategy when linked explicitly to knowledge management or marketing disciplines.

Concurring, Calof et al. (2018) result indicated that respondents acknowledged the benefits and essential role of CI in the Marketing Strategy Formulation (MSF) process—citing a challenge in integrating CI into MSF. Moreover, Maritz and Du Toit's (2018) investigation revealed no connection between CI, formulation of deliberate and emergent strategies, communication and implementation amongst the literature themes (Please refer to themes 1-6 in Figure 3.11 aforementioned).

In sum, CI is a strategy that equips organisations with competitive insights into the external environment. CI also studies strategic information and assists organisations with this information to anticipate market trends and innovation (Foley & Guillemette, 2017).

Therefore, CI strategy is significant for organisations' decision-making processes and capabilities to surpass disruptive innovation in the highly contested business environment (Vargas & Perez, 2017). CI can identify overlooked customer needs in the marketing strategy content. In pursuit of business strategy, CI analyses emerging customer needs that the competition has recognised as one of its core competencies over its industry.

This view connotes that CI is key to marketing and business strategies (Alnoukari & Hanano, 2017; Bartes, 2014c; Calof & Wright, 2008; Calof et al., 2018; McGonagle, 2016). CI is equally central to the survival of organisations as it analyses the environment, competitors, and markets and provides insights into the strategic decisions and directions needed to anticipate competitor actions and drifts in the markets (Maritz & du Toit, 2018; Sewdass & Du Toit, 2014).

CI plays a principal role in assimilating all the strategic management processes within organisations; therefore, it provides rational planning to ensure the successful integration and alignment of the deliberate and emergent strategies in different phases of the strategic planning process (Maritz & du Toit, 2018).

Successfully integrated competitive business and corporate strategies are imperative for organisations to get higher flexibility and agility in today's highly competitive environment (Alnoukari & Hanano, 2017). For that reason, it is necessary to explore the effect of CI on sustainable competitive advantage.

The following section explores the relationship between CI and sustainable competitive advantage.

3.5 Competitive Intelligence and Sustainable Competitive Advantage

Today's competitive business environment means organisations struggle to survive: to stay competitive requires the conscious, continuing seeking of competitive advantage. This view implies a growing need for organisations to exploit their differentiators by remaining creative, innovative, and competitive while maintaining the resilience to survive in turbulent times.

Organisations with a visible presence in the market will gain a competitive advantage and reap better benefits from the competition (Porter, 1988). Meanwhile, CI plays a key role in protecting the competitive advantage assimilated by organisations (Supardi & Herawan, 2020). SCA contributes immensely to above-average profitability (Supardi & Herawan, 2020). This view shows that organisations attain SCA if they realise above-average performance over sustained periods (Ritthaisong, Johri & Speece, 2014).

Therefore, SCA is the value created by organisations to drive market competition through innovation (Kuncoro & Suriani,2018). In essence, SCA depends on strategic advantage, which offers favourable terms for the organisation to achieve superior results relative to the competition (Hakkak & Ghodsi, 2015).

To sustain competitive advantage, organisations should take advantage of opportunities and threats from growing local and global competition, better-informed customers, higher expectations and technological advances while creating more value for customers (Eidizadeh et al., 2017). In that way, organisations should identify opportunities that create different competencies to gain greater economic benefits than the competition (Supardi & Herawan, 2020).

The agility of organisations' adjustment to changes in the competitive environment upholds competitive advantage for these organisations and creates greater economic value than the competition (Varela, Gonzalez-Perez & Velez-Ocampo, 2014).

Organisations that can attract customers and defend themselves against the competitive forces in external environments have a competitive advantage and a leading-edge comparative to the competition (Porter, 1980). This view illustrates that as organisations acquire a set of traits to outpace their competition, they gain a competitive advantage (Wang, 2014).

The current competitive business environment requires organisations to make the most of KM and CI to create and sustain competitive advantage (González-Loureiro, Vila Alonso & Schiuma, 2015). This view concurs with Ghannay and Mamlouk (2015), who uphold that due to the intensification of competitive pressure in business, organisations should pay attention to activities such as collecting, filtering and disseminating information about markets and competitors' actions.

Meanwhile, strategic intelligence is vital for organisations to create and transfer knowledge that can be used for effective decision-making and take full advantage of futuristic challenges and opportunities to attain SCA (Heiko, Bañuls, Turoff, Skulimowski & Gordon, 2015).

Essentially, organisations should implement CI to adapt and survive in the competitive environment and respond to the challenges and opportunities created by this environment (Adidam et al., 2012). Organisations can maintain SCA if they have clearly defined systems that transform data into CI (Stefanikova et al., 2015).

According to Porter (1985), organisations that process intelligent information and knowledge attain a competitive advantage. BI systems are, therefore, proficient at structuring large volumes of information so that it is accessible within the organisation to create a competitive advantage (Petrini & Pozzebon, 2009). Equally, an effective BI system improves the quality of the organisation's strategic and operational planning and throughput efficiencies for decision-making (Singh & Samalia, 2014).

These days, organisations obtain knowledge and information about their operating environment to gain a competitive advantage and make important decisions in the intensely contested business environment (Rajnoha, Stefko, Meriková & Dobrovic, 2016).

Meanwhile, knowledge stimulates production in the mainstream economy, and it aids organisations in achieving economic performance to maintain a competitive advantage (Rajnoha et al., 2016). In essence, organisations use knowledge to strengthen their competitiveness for customers and employees (Singh & Samalia, 2014).

Stefanikova et al. (2015) highlight that whilst there is a need to focus on big data, organisations struggle to collect relevant data and information. Therefore, organisations need to use CI to transform data into intelligence to maintain a competitive advantage (Stefanikova et al., 2015). Yet, Rajnoha and Lorincová (2015) maintain that it is vital for organisations to integrate decision support in their operation and work systems to fast-track important decisions and gain a competitive advantage.

In the same way, Hagiu and Tanascovici (2013) point out that CI software allows sharing and diffusion of relevant information throughout the organisation to facilitate decision-making and obtain and maintain a competitive advantage. CI activity integrates information and knowledge from the internal and external environment through a unique process to facilitate intelligent information flow throughout the organisation to obtain and maintain a competitive advantage in the business environment (Stoica, 2017). This view validates that the application of CI makes things easier to accomplish competitive advantage (Safarnia, Akbari & Abbasi,2011).

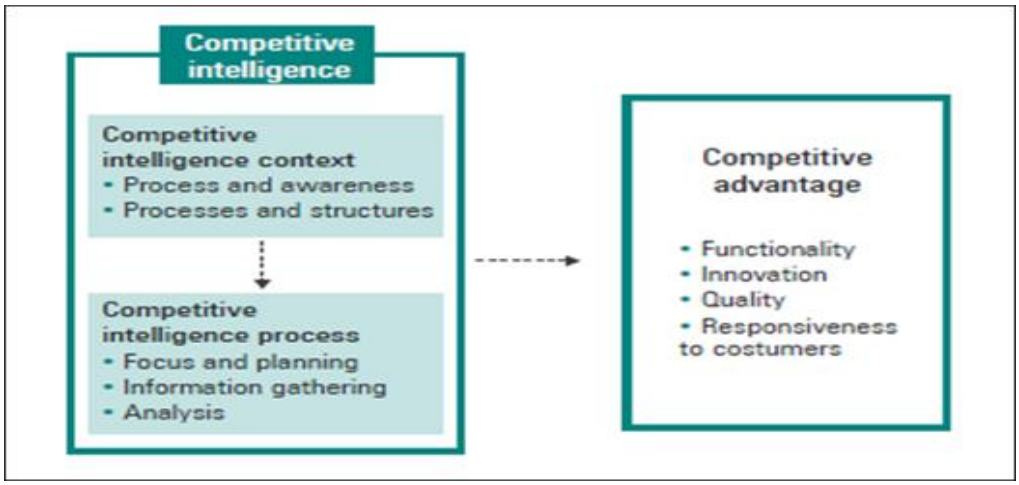
CI is about knowledge and information about the environment in which organisations operate, enabling organisations to gain a competitive advantage and compete successfully against the competition (Brody, 2008). Waithaka, Bula and Kimencu (2016) put it differently that target-orientated CI is knowledge about the organisation's environment that has implications for competitors operating in its niche market.

Furthermore, Waithaka et al. (2016) maintain that target-orientated CI empowers organisations to focus on competitors' current activities, capabilities, plans and intentions to achieve competitive advantage.

Therefore, CI is a tool that supports organisations to gain a competitive advantage to outstrip competition (Ahmed, Ahmad, Khoso, Arif & Palwishah, 2014). Hemmatfar, Salehi & Bayat (2010) likewise found that strategic information systems aided competitive advantage in organisations and contributed to strategic goals, significantly increasing performance and productivity.

Another study by Amiri et al. (2017) found that CI is a tool for gaining a competitive advantage in the insurance industry. The research results showed the effect of CI on developing competitive advantage. Furthermore, Amiri et al. (2017) developed a conceptual model integrating CI and competitive advantage. In this mixed model, CI directly affects CI processes in tandem with CI processes influencing competitive advantage (See Figure 3.12 below).

Figure 3.12: Conceptual model for CI and Competitive Advantage



Source: Amiri et al. (2017, p.180)

Recent research by Nte, Omede, Enokie and Beinose et al. (2020) found that CI positively influenced competitive advantage. Furthermore, their study showed that CI assists organisations in making strategic decisions that inspire productivity—manage the competitive environment and promote competitive fitness and organisational performance.

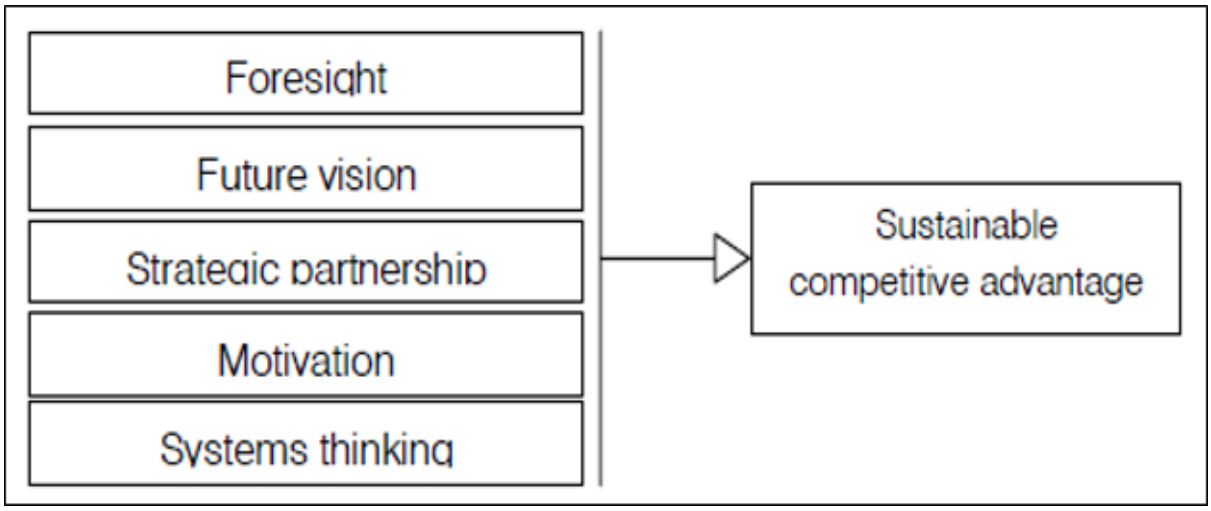
A study by Nte et al. (2020) discovered that CI could positively affect the organisation's growth, higher quality, and performance. While Agha, Atwa and Kiwan (2014) similarly in their study concluded that strategic intelligence positively impacts organisational performance.

Consistently, research findings by Waithaka et al. (2016) showed that target-oriented CI practices had a positive and statistically significant relationship with the performance of organisations listed in the Nairobi securities exchange. These results signify that organisations performing CI activities have a greater chance of gaining a competitive advantage.

Equally, Uzoamaka et al. (2017b) revealed a substantial association between strategic intelligence and business success; Alhamadi's (2020) analysis consistently found a statistically significant effect of strategic intelligence dimensions on SCA.

Furthermore, Alhamadi (2020) clarified that strategic intelligence, benchmarked with foresight, future vision, strategic partnership, motivation, and systems thinking, led to SCA. Based on the study's hypothesis and the findings, he proposed a theoretical model which illustrated the causative relationship between all the strategic intelligence dimensions with SCA (see Figure 3.13 below).

Figure 3.13: Theoretical Model for Strategic Intelligence Dimensions and SCA



Source: Alhamadi (2020, p. 4)

Moreover, Muritala and Ajetunmobi's (2019) research showed a positive relationship between CI and the competitive advantage of selected insurance companies in Nigeria. Yet, previous research by Charity and Joseph (2013) revealed a significant relationship between CI and strategic advantage.

In contrast, the research results by Cory (1996) highlighted that not all the CI activities resulted in the attainment of SCA. CI anticipates market developments by empowering organisations to respond proactively to the severely contested competitive business environment. In tandem, CI aids strategic decisions and organisational performance (Johns & Van Doren, 2010 cited in Nte et al., 2020, p.78; Supardi & Herawan, 2020).

In addition, Supardi and Herawan (2020) advocate that CI enables business processes that support competitive advantage and superior performance. CI then aids in introducing new products and developing new markets (Supardi & Herawan, 2020).

Relatedly, Uzoamaka et al. (2017b) highlight that strategic intelligence provides insights about future trends that are more likely to impact organisations to remain competitive in today's turbulent and dynamic environment.

Therefore, organisations need strategic intelligence to maintain a presence in the business environment (Abd, Abbas & Khudair, 2019). CI notably contributes significantly to the growth and performance of organisations. Equally, CI supports organisations in attaining and maintaining a competitive advantage relative to industry peers (Nte et al., 2020). This view shows a significant role played by CI in driving competitiveness and organisational performance (Uzoamaka et al., 2017a).

CI enables new market segmentation and development along with product and service innovation. In so doing, it supports competitive advantage and organisational performance (Porter, 1980). Nasri's (2012) study revealed that organisations tend to develop CI processes that yield SCA. Organisations that succeed in implementing formal and structured CI processes addressing core issues will gain a competitive advantage over their rivals (Hagiu & Tanascovici, 2013).

According to Syapsan (2019), sources of competitive advantage comprise company resources, capabilities and external factors impacting the survival of organisations. In essence, managers should take appropriate actions to normalise processes and structure organisational resources to ensure they are well managed in the market to gain SCA (Castro & Giraldi, 2018). CI consists of capabilities that always direct organisations to attain superior performance over their rivals (Hamidizadeh et al., 2014).

Organisations should obtain extensive knowledge about their opponents' competitive advantage in achieving and maintaining SCA (Muritala & Ajetnumobi, 2019). CI employs internal and external resources to produce intelligent information timeously for organisations to attain SCA (Santos & Correia, 2010). This view is congruent with research by Schiefer (2013), indicating that respondents widely accepted that competitor information leads to superior resource allocation and competitive advantage.

Bulley et al. (2014) also uphold that organisations will prosper and gain advantage only if they use information and knowledge assimilated about competitors, customers, and the external environment intelligently. In essence, information is an effective game-changer and critical for decision-making. It enables organisations to thrive in challenging business

environments, meaning that organisations possessing reliable and significant information maintain SCA (Bartes, 2014a).

Therefore, organisations should use intelligent information to sustain themselves and be in touch with the dynamic business environment (Bulley et al., 2014). Equally important, CI acquires appropriate and accurate information about competitor actions and plans for supporting management with effective decisions (Peltoniemi & Vuori, 2008). Most executives then rely on CI information for decision support to stay ahead of the competition and make actionable decisions (Ezenwa, Stella & Agu, 2018). This view illustrates that CI contributes significantly to business management and practice.

Organisations use CI to keep up with rapid changes in the business environment (Bulley et al., 2014; Ezenwa et al., 2018). For that reason, CI supports strategic planning and management processes in organisations. In doing so, CI investigates the competitive environment to improve tactical and strategic decision-making throughout the organisation (Ezenwa et al., 2018). CI resides within the domains of strategic management permitting organisations to realize SCA (Casado Salguero, Fernández Gámez, Aldeanueva Fernández & Ruíz Palomo, 2019; Supardi & Herawan, 2020).

Similarly, Ezenwa et al. (2018) advocate that CI supports strategic management processes within the organisation. CI improves organisational communication, knowledge, and performance to accomplish concrete strategic outcomes (Ezenwa et al., 2018; Salguero et al., 2019; Hamidizadeh et al., 2014).

CI has then become a technique that organisations use to achieve competitive advantage and performance (Saayman et al., 2008). This implies CI's significant role in the organisation's management and strategic planning processes. In essence, CI develops and predicts markets to facilitate competitive advantage for organisations (Ezenwa et al., 2018). CI plays a significant role in strategic management, and it has become an effective technique that enhances and enables organisations to sustain a competitive advantage over competitors (Ghannay & Mamlouk, 2015). Similarly, Stenberg and Vu-Thi (2017) advocate that CI permits organisations to progress with emergent strategies to develop a competitive advantage.

CI also empowers organisations to thrive and gain a competitive edge in the market (Bulley et al., 2014). Thus, CI is one of the most important techniques for facilitating competitive advantage (Sepahvand et al., 2016; Hamidzadeh et al., 2014). Meanwhile, CI diagnoses competitor actions and responses to the market, and it empowers organisations to predict and develop markets to attain SCA (Hamidizadeh et al., 2014).

Essentially, CI adds utmost value to organisations and their strategic objectives (Stenberg & Vu-Thi, 2017). In effect, the value created by CI processes includes a series of systematic activities driven by the organisation's intelligent needs to achieve a competitive advantage (Cloutier, 2013).

According to West et al. (2015), CI obtains actionable insights about numerous activities in the business environment for organisations to develop and sustain competitive advantage. Additionally, organisations use CI to gain information from competitors and maintain a competitive edge during erratic times and unfavourable market conditions (Amiri et al., 2017).

Therefore, organisations must be vigilant and plan ahead of the competition to sustain competitive advantage (Ghannay & Mamlouk, 2015). Furthermore, organisations need to develop CI to gather information about external competitor activities and integrate this information internally in the best way (Johnson et al., 2016).

In that way, organisations will figure out threats and weaknesses they need to overcome from their competitors and which strengths to take advantage of to capture opportunities and devise strategies to adapt and protect them from gaining competitive advantage (Stenberg & Vu-Thi, 2017).

Consequently, organisations will attain a peerless competitive advantage over their rivals (Wright, 2014). Stenberg and Vu-Thi (2017) modified a CI TOWS matrix model, demonstrating that CI enhances the reliability and feasibility of strategic options to realise competitive strategies that improve the organisation's competitive advantage and sustainability (See Figure 3.14 hereunder).

Figure 3.14: Competitor Intelligence TOWS Matrix

Source: (Stenberg and Vu-Thi, 2017, p.7)

CI significantly influences organisations' strategic advantage and development (Johnson et al., 2016). This view supports one made by McGonagle and Misner-Elias (2016), who advocated CI as a link enabling an organisation to adapt its competitive strategy to attain a competitive advantage. Moreover, this view highlights the significance of synergising knowledge and CI to make effective decisions bringing about competitive advantage (Shujahat et al., 2017).

In bringing about competitive advantage, organisations should create a compelling and inimitable value proposition that meets different customers' needs. That way, organisations gain a competitive advantage from understanding customer analytics and taking advantage of the opportunities within the customer value chain in creating and delivering products or services (Porter & Kramer, 2019).

This view means successful organisations overlap boundaries and develop marketplace advantages relative to their competition. In so doing, organisations attempt to develop a process that allows innovating and modifying existing products in anticipation of market changes (Arnett, Sandvik & Sandvik, 2018).

This observation supports recent research by Eidizadeh et al. (2017), who found that business intelligence positively impacts knowledge sharing, organisational innovation, and competitive advantage. CI influences different variables such as strategy, SCA and organisational performance. Essentially, CI enhances internal communication, knowledge, and strategic plans to increase organisational performance (Rezaie Dolatabady, Zeinali & Shekarchizadeh, 2011; Hamidizadeh et al., 2014; Ezenwa et al.,2018; Casado Salguero et al., 2019).

Equally, CI is not associated with BI, KM and other knowledge-based systems since these systems reside within the framework of CI (Tanev & Bailetti, 2008). This view designates that CI provides infrastructure that forms the foundation of competitive advantage for all the knowledge-based systems to strengthen their sustainable capacity and capabilities for attaining CI (Dishman & Calof, 2008).

CI processes accumulate competitor information and environments to improve organisational performance (Wright, Fleisher & Madden, 2008). CI also gains appropriate information from the competitive environment explicitly used to improve planning and decision-making (Kotler, Keller, Brady, Goodman & Hansen, 2019). This view signifies that CI creates awareness and provides insightful knowledge about the business environment in which executives make effective decisions (Sharp, 2012).

Also, this view correlates with Nazar and Seidali Route's (2017) finding that knowledge of market situations and foreknowledge of competition, technology, and strategy had a positive and significant relationship with organisational flexibility. Furthermore, their study showed a significant positive relationship between CI and organisational flexibility. This finding indicates that successfully deployed CI provides executives with knowledge for making decisions to ensure organisations sustain competitive advantage in the macro-environment (Ahmad, 2015).

In another study, Caseiro and Coelho (2018), and Yin (2018) pointed out causative relationships between CI and organisational performance, asserting a critical role in influencing executives towards decision-making that will change the destiny of

organisations. Succinctly, organisations continue to face the severity of the competitive environment, making it challenging to maintain SCA (Nenzhelele & Pellissier, 2014).

Organisations should therefore monitor business environments, gather intelligent information, and make accurate and immediate decisions to confront different opportunities and market threats to improve their performance compared to competitors (Amiri et al., 2017).

CI is the knowledge and information about the environment in which organisations operate, thus enabling them to compete effectively and gain a competitive advantage (Brody, 2008). In this manner, CI monitors the competitive environment. Furthermore, it provides organisations with intelligent information and insights about competitor activities to gain a competitive advantage in the fiercely contested business environment (Ahmed et al., 2014).

CI's primary functions and objectives are noticeably to maintain and develop distinctive competitive advantages for organisations (Dishman & Calof, 2008). Nevertheless, CI is internationally recognised as a tool that assists organisations in upholding their competitiveness. It also supports management decision-making in knowledge-based organisations (Hagiu & Tanascovici, 2013). Notably, the purpose of CI is to help and lead management actions and decisions within organisations (Hagiu & Tanascovici,2013).

3.6 Conclusion

This chapter reflected on theories and models used to explain CI and strategy management. The chapter further discussed the relationships between CI and SCA. The next chapter presents the study’s conceptual model regarding the relationships proposed between the constructs under investigation.

Chapter Four: Conceptual Framework and Hypothesis Development

4.1 Introduction

With the rapid technological advances, information technology permits organisations to respond swiftly to changes in the business environment. In doing so, most organisations have tailored effective business processes that identify new opportunities to improve their agility and performance (Chakravarty, Grewal & Sambamurthy, 2013).

As social networks generate big data from millions of users, the abundance of information accumulated from social media and web-based sources attracts organisations to these channels as sources of CI (Markovich et al., 2019, p. 708). Therefore, organisations must continually improve intelligence to strengthen their capabilities in the current global business environment (Hamad & Yozgat, 2017). Furthermore, Hamad and Yozgat (2017) mention that performing intelligence safeguards the organisation's success in the long-term.

CI is an elegant system that identifies competitors' intentions and risks to expose an organisation to threats. In addition, it accelerates the organisation's strategic planning processes (Stefanikova et al., 2015). CI also plays a significant role in developing and deploying national and corporate strategies (Dishman & Calof, 2008; Salguero & Quintero, 2016); it augments knowledge creation and intelligence for organisations (Bisson, 2014).

Essentially, CI analyses information gathered to safeguard organisations from economic espionage. In addition, it ensures collaboration among organisations to ensure their survival in the long-term (Maune, 2019). CI is a process through which information about the external environment is collected, analysed, and communicated to assist strategic decision-making (Dishman & Calof, 2008).

This chapter proposes a conceptual framework that organises and directs this research. The literature review in this present and previous chapters serves as the theoretical foundation for this study's conceptual framework and hypotheses.

The following chapter uses this study's conceptual framework to design the research methodology.

4.2 Conceptual Framework

Organisations are advancing their business processes to eliminate constraints in their operation to survive the turbulent and highly competitive global environment (Popovič et al., 2018). For this reason, organisations should adopt long-term orientation and take strategic actions to acquire and analyse information to sustain competitive advantage (Altinay et al., 2016).

Organisations should develop a successful analytics framework that identifies constraints and transforms information into insights that focus on action (Hagel, 2015). Therefore, CI affects decision-making and contributes immensely to the organisation's operation and performance (Ahearne, Lam, Hayati & Kraus,2013).

The prevailing research studies on CI have highlighted that CI is critical for collecting and distributing information along with strategic management tools aimed at scanning the environment among analysing market trends for effective decision-making processes (Amiri et al.,2017; Bartes, 2014 a; Bartes, 2014b; Bartes, 2014 c; Franco et al.,2011; Pellissier & Kruger, 2011; Sewdass & Du Toit, 2014).

Some literature shows that CI is critical in formulating and developing business strategies (Bartes, 2014c; Calof & Wright, 2008; Maritz & Du Toit, 2018; Sewdass & Du Toit, 2014; Vidigal, 2013). This study also develops a model that entrenches CI throughout the organisation's value chain.

For CI to contribute significantly to the organisation's operation, leadership acceptance, awareness and support, and a culture of competitiveness with employee involvement set in, thus making CI practices successful all over the organisation (Saayman et al., 2008).

Entrenching CI practices requires leadership attention and awareness (Wright, Fleisher & Allard, 2008). Additionally, previous studies have highlighted the significant role played by strategic orientations in driving superior performance.

Specifically, the research findings by Lo, Wang, Wah and Ramayah (2016) indicated that technology and entrepreneurial orientation correlated to an organisation's non-financial and financial performance. However, Lo et al. (2016) found that top management support is only positively associated with financial performance. In contrast, Lo et al. (2016) found no relationship between customer focus, employee orientation and organisational performance.

Equally, Salaheldin's (2009) research showed that leadership, top management support, and organisational culture were strategic factors that significantly affected overall organisational performance. Therefore, strategic orientation directs and influences business activities to exploit opportunities to gain and sustain competitive advantage (Hakala & Kohtamäki, 2011).

Strategic orientation represents an external view of the fit between the organisation's strategic choices and operational environment, while dynamic capabilities are inward-looking. The choices focus on integrating and revitalising the organisation's resources (Zhou & Li, 2010). Strategic orientation guides the organisation to interact with customers, competitors, and technology in the rapidly changing business environment (Day, 1994; Gatignon & Xuereb, 1997).

This current chapter develops this study's conceptual framework and hypotheses after reviewing the relevant literature in Chapter 3. Figure 4.6 illustrates this study's conceptual model with the hypothesised relationships between the constructs.

This study's integrated conceptual model is thereby drawn from three streams of research, namely competitive intelligence embeddedness by Markovich et al. (2019); the Technology Organisation Environment framework modelled by Duh and Fabiao (2018); and the Information Acceptance Model by Erkan and Evans (2016) respectively.

This conceptual framework covers this study's independent, dependent, mediating, and moderating variables and their relationships. In addition, the 17 hypothetical relationships established in this study's integrated conceptual framework are presented.

4.2.1 The TOE Framework

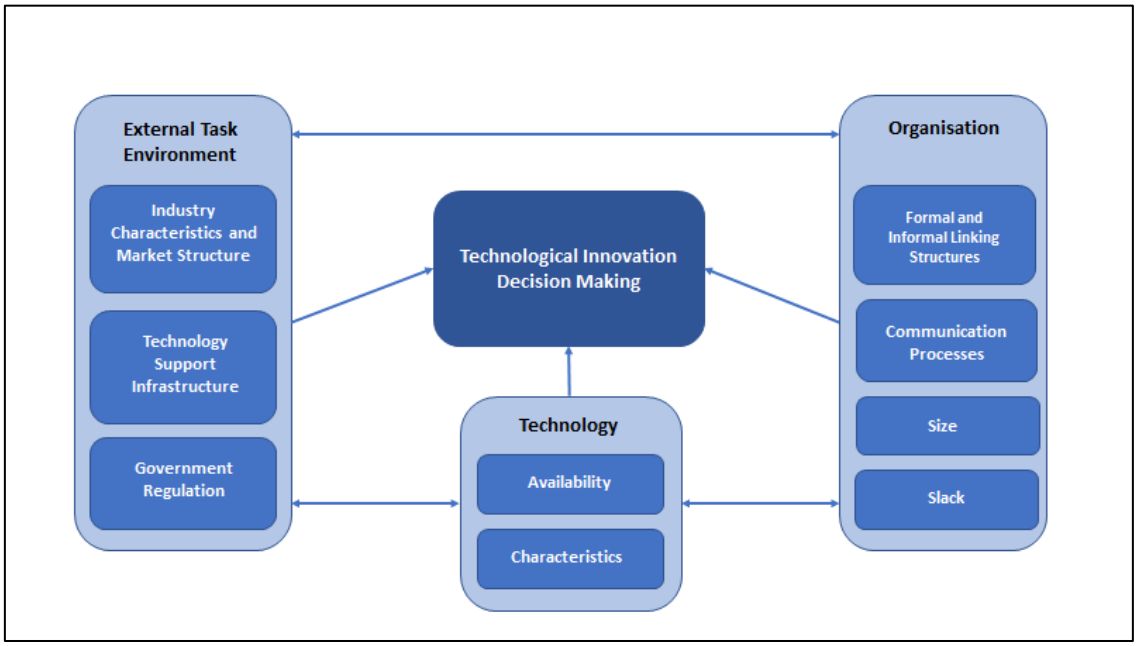
With external Keys Success Factors (KSF) in the market, defining the value chain of business activities. Essentially, organisations must tailor processes and perform business activities well.

Distinctive capabilities and organisational processes are closely intertwined (Day,1994, p.38). Specifically, distinctive capabilities permit organisations to deliver superior value for customers. Furthermore, distinctive capabilities effectively allow business activities and processes to prune operational costs (Day,1994).

On the other hand, technology adoption rests on organisational and environmental factors that profile technology adoption within an organisation's value chain (Ghobakhloo, Benitez-Amado & Arias-Aranda, 2011).

Tornatzky and Fleischer (1990) developed the Technology Organisation Environment (TOE) framework to analyse the propensity of an organisation to adopt technologies using technological, organisational, and environmental contexts to investigate factors that influence technological innovation adoption and the implementation processes within organisations (See Figure 4.1 below). According to Tornatzky and Fleischer (1990, p.154), these three contexts provide both limitations and possibilities for technical innovation.

Figure 4.1: The TOE Framework



Source: (Tornatzky and Fleischer, 1990, p.154)

According to Tornatzky and Fleischer (1990, pp.152-154), technological context describes both existing and new technologies in use within the organisation, including the technology that is available in the market and currently used by organisations (Gupta, Seetharaman, Arumugam & Raj, 2013; Lin & Chen, 2012; Oliveira, Thomas & Espadanal, 2014).

The technology comprises variables that influence individuals, organisations, and the industry's innovation adoption (Claycomb, Iyer & Germain, 2005; Huang, Janz & Frolick, 2008). Yet, some researchers have employed many variables other than innovation attributes (Gangwar, Date & Root, 2014).

These studies found significance in variables such as systems assimilation, trialability, complexity, perceived direct and indirect benefits and standardisation. In contrast, these studies found insignificance in observability variables (Hossain& Quaddus, 2011;

Musawa & Wahab, 2012; Jang, 2010; Ramdani, Chevers & Williams, 2013; Thiesse, Staake, Schmitt & Fleisch, 2011).

Equally, Tornatzky and Fleischer (1990, pp.152-154) believe that organisational context refers to the scope, size and amount of slack resources, as well as managerial beliefs (Salwani, Marthandan, Norzaidi & Chong, 2009). Studies have found statistical significance and insignificance amongst the variables within the organisational context domain (See for example, Hossain & Quaddus, 2011; Musawa & Wahab, 2012; Huang et al., 2008; Jang, 2010; Lin & Lin, 2008; Ramdani et al., 2013; Wang, Wang & Yang, 2010).

In addition, Tornatzky and Fleischer (1990, pp.152-154) sustain that the environmental context is the competitive landscape where companies in a similar industry deal with governments. In essence, the external environment focuses on areas where an organisation conducts their operations and prioritises factors that influence the industry, such as government incentives and regulations (Salwani et al., 2009).

According to Depietro, Wiarda and Fleischer (1990, pp.169-171), the environment context includes variables related to the industry characteristics, which manifests in rivalry, and relationships with stakeholders through different stages of the industry life cycle.

Furthermore, in the environmental context domain, significance was found in various variables, with government regulation showing insignificant (Hossain & Quaddus, 2011; Huang et al.,2008; Jang, 2010; Lin & Lin, 2008; Musawa & Wahab, 2012; Salwani et al.,2009; Thiesse et al., 2011; Wang et al., 2010; Zhu, 2004).

Quite a lot of studies applied the TOE framework on which they made discoveries in relation to company size, top management support, social influence, and trading partner pressure (See for example, Alshamaila, Papagiannidis, Savvas & Li, 2013; Gangwar, Date & Ramaswamy, 2015; Lin & Chen, 2012; Low, Chen & Wu, 2011; Wu, 2011).

The Tornatzky and Fleischer (1990) (TOE) framework has arisen from a broad theoretical viewpoint on Information Technology (IT) adoption, thereby connecting the technological,

organisational, and environmental elements to the complete value chain of the organisation's operation (Zhu & Kraemer, 2005).

The TOE framework in Figure 4.1 advocates that it is used to gather insights about organisational and market factors that inspire organisations to entrench and adopt environmentally friendly measures together with innovative business practices (Angeles, 2014; Sila, 2013). The TOE framework outlines three characteristics of a company's environment that determine how it accepts, implements, and uses technological innovation (Zhu & Kraemer, 2005, p.63). Indeed, the TOE framework denotes that organisational, technological, and environmental factors are key drivers that accelerate the adoption of various technologies by the organisation, its employees, and its leadership (Duh & Fabiao, 2018, p.16).

The TOE framework incorporates technological, organisational, and environmental contexts, using technology to create value for organisations (Gutierrez, Boukrami & Lumsden, 2015). Therefore, the TOE framework is commonly applied in understanding organisational and technological adoption (Bradford, Earp & Grabski, 2014, p. 152; Hameed, Counsell & Swift, 2012,p. 362; Hsu, Ray & Li-Hsieh, 2014,p. 476; Oliveira & Martins, 2010, p.110).

The inclusion of technological, organisational, and environmental variables has made the TOE framework frequently and mainly used in comparison to similar technology adoption models (See for example, Dwivedi, Papazafeiropoulo, Ramdani et al., 2009; Hossain & Quaddus, 2011; Oliveira & Martins, 2010; Zhu & Kraemer, 2005).

Essentially, the TOE framework provides a holistic picture about the organisation's value chain activities and factors that influence business decisions to the pursuit of adopting technology as well as developing effective organisational capabilities to manage business activities effectively (Lin & Lin, 2008; Salwani et al., 2009; Wang et al., 2010; Zhu, 2004).

Some studies have used the TOE framework in different contexts. For example, Alshamaila et al.(2013), Gangwar et al. (2015), Gutierrez et al.(2015), Gupta et al.(2013),

Hsu et al.(2014), Lian, Yen and Wang (2014), and Oliveira et al.(2014) investigated TOE framework in a cloud computing environment.

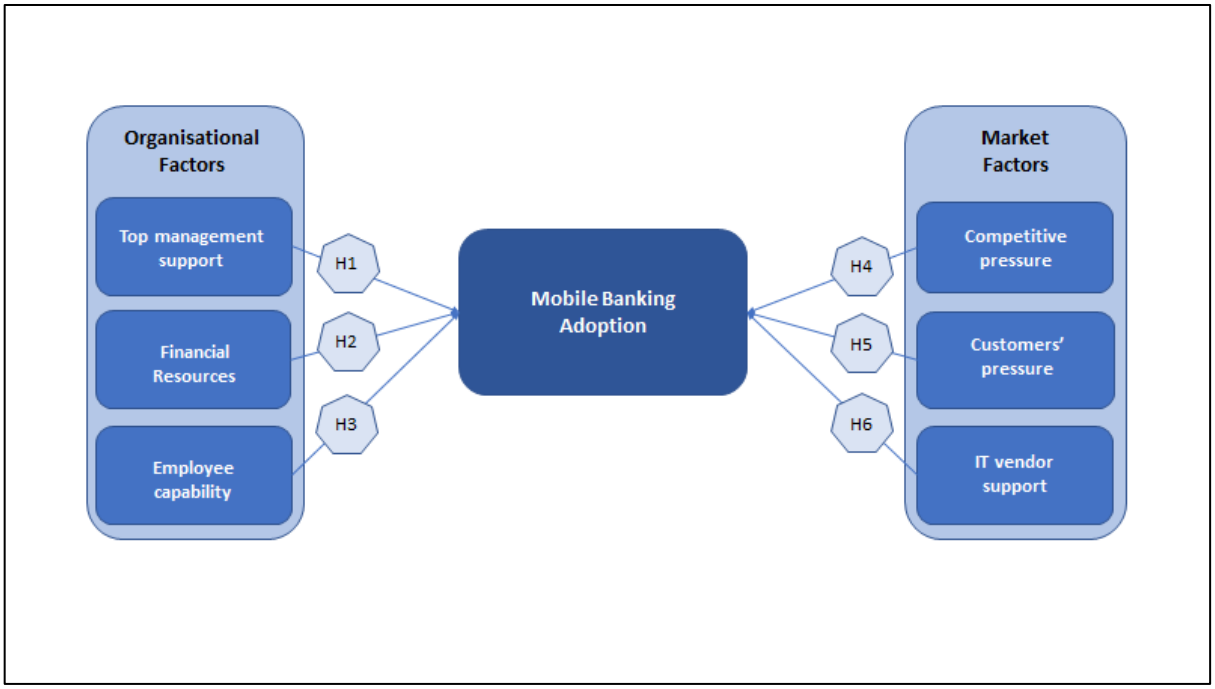
While other studies employed TOE in Enterprise Resource Planning (ERP) in organisations (Bradford et al.,2014; Ruivo, Oliveira & Neto, 2014). Also, other studies on TOE were in the enterprise applications (Ramdani et al., 2013). This again signifies that the TOE framework is extensively used due to its comprehensive structure and sound theoretical basis for understanding organisations' technological adoption behaviour (Bernroider & Scmöllerl, 2013, p.142).

Another study by Duh and Fabiao (2018) employed the TOE framework to understand organisational and market factors behind the success of mobile banking adoption in Mozambique (see Figure 4.2 hereunder).

Duh and Fabiao (2018) investigated mobile banking adoption in Mozambique markets. This study reported a significant impact on vendor support, customer, financial resources, and competitive pressure, showing the most significant considerable impact relative to all items under investigation.

Furthermore, this study's results corroborate results from Gangwar et al. (2015), who found that competitive pressure and partner support significantly influence cloud computing. In addition, Gutierrez et al. (2015) showed that out of eight factors examined, complexity, competitive pressure, trading partner pressure and technology had a significant influence on the adoption decision of cloud computing services.

Figure 4.2: Mobile Banking Adoption Model



Source: (Duh and Fabiao, 2018, p.19)

Equally, Duh and Fabiao (2018) found that top management support and employee capability were insignificant compared to other items under market and organisational factors. This result implied that top management support was no longer an important driver with organisations acquiring and adopting technology at a reasonable cost.

Concurring, some studies also found no need for top management support to adopt technology (Gutierrez et al., 2015; Lian et al., 2014). In contrast, other research studies found that top management support contributed significantly to technology adoption (Gangwar et al., 2015; Sila, 2013).

These varying results show that the TOE framework, even if it is used in various studies, has its limitations relating to how variables are selected and empirically tested in different environmental contexts (Aboelmaged, 2014, p.641; Ismail & Ali, 2013, p.130; Ramdani & Kawalek, 2008, p.148). The TOE framework is generic, and it lacks explicit major

constructs since it only categorises variables suggesting that it does not represent an integrated conceptual model (Dedrick & West (2003),

Meanwhile, variables of the framework differ in most studies with varying contexts (Gangwar et al., 2014; Riyadh, Akter & Islam, 2009; Wang et al.,2010). The TOE modelled by Duh and Fabiao (2018) in Figure 4.2 showed that other variables had no significant effect.

Organisational capabilities yet improve an organisation's agility, flexibility, and scalability. This result highlights that the TOE framework needs strengthening by integrating it with other models with clear constructs (Gangwar et al., 2015).

Given that the variables of the TOE framework vary across different contexts with their level of significance, for instance, Duh and Fabiao (2018) found significance and insignificance amongst the variables under organisational and market factors studied.

Duh and Fabiao's (2018) study emphasised that a common set of variables could not be generalised to explain the application of technology adoption in a different context (Gangwar et al., 2015, p.110). Based on some criticisms against the TOE framework, this study modified the use of Duh and Fabiao's (2018) model.

As a result, this study has employed cognitive and sociological variables to enrich the TOE framework modelled by Duh and Fabiao (2018) to achieve the research objectives. This study has introduced different variables in developing the integrated model by adding some constructs to make the proposed model more relevant to this research.

Furthermore, this study has also introduced a set of identified variables to facilitate an integrated model that provides insights about the organisation's value chain activities that gather and analyse intelligence information to stimulate the firm's performance.

Thus, integration of the TOE framework, information acceptance and competitive intelligence embeddedness models transform competitor and industry information into actionable strategic knowledge (Bernhardt, 1994, p.13).

4.2.2 Information Acceptance Model

The plethora of online platforms permits people to share quantities of information online; in the interim, they use online platforms to search for relevant and valuable information (Wang, 2016, p.618). Organisations that use CI to transform this information into actionable intelligence may prosper and succeed in the fiercely contested business environment.

Previous researchers like Nonaka (1994) have focused on how people adopt and internalise the information they receive. In comparison, others have applied the Technology Adoption Model (TAM) and Theory of Reasoned Action (TRA) to understand how information affects people (Ajzen, 1985; Davis, 1989; Fishbein & Ajzen, 1975).

The TAM theory by Davis (1989) was derived from Fishbein and Ajzen's (1975) TRA model. It is a widely accepted theory that identifies individuals' behaviours in accepting new technologies. However, Ayeh (2015) advocates that TAM might not deliver an insightful understanding of users' attitudes and intentions where separate individuals generate information.

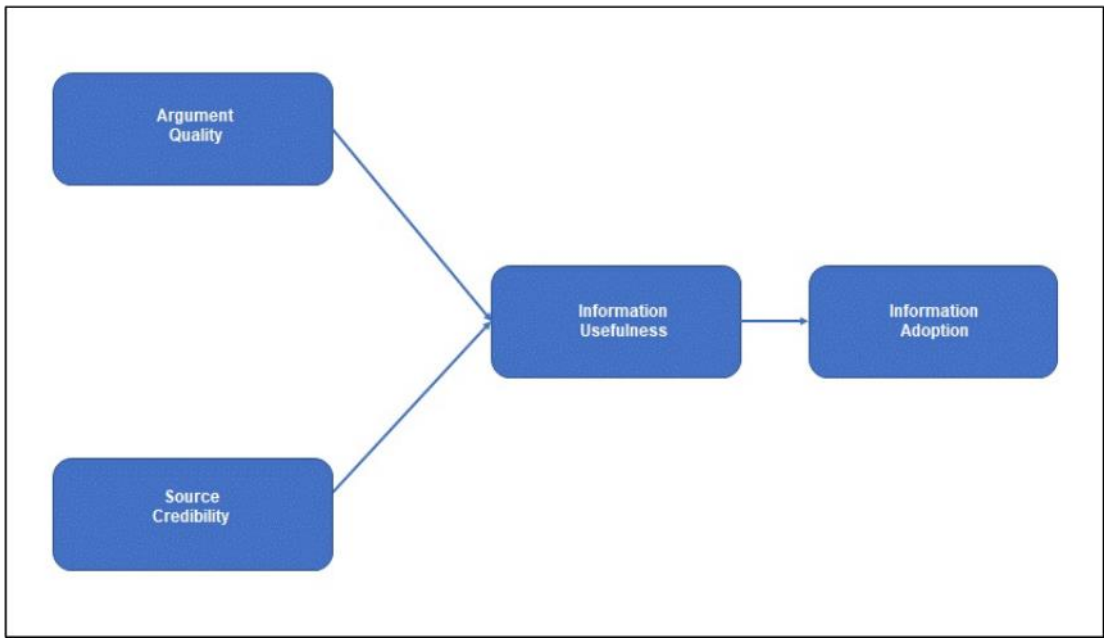
In contrast, the Elaboration Likelihood Model (ELM) is suitable for explaining how information receivers are affected by the information contained in a message that is likely to change their attitudes and communication (Petty & Cacioppo, 2012).

Cheung et al. (2008), Petty and Cacioppo (2012), and Shu and Scott (2014) have pointed out that communication is delivered from both the central route and the peripheral routes of information. Furthermore, they argue that the central route relates to the message's core, whilst the peripheral route handles difficulties not directly linked to the message's substance. The ELM suggests that people act by communication obtained from central and outer information routes (Shen, Cheung & Lee, 2013; Sussman & Siegal, 2003).

According to Erkan and Evans (2016, p.49), the IAM model consists of four components (Please refer to Figure 4.3 below). In addition, Erkan and Evans (2016) state that including these components in the IAM model describes how humans are impacted by computer-

mediated communication information. Figure 4.3 depicts the IAM paradigm, emphasising information quality, trustworthiness, and utility (Erkan & Evans, 2016).

Figure 4.3 Information Adoption Model



Source: (Sussman and Siegal, 2003, p.11)

Cheung et al. (2008) employed the original IAM model to investigate factors that affected the acceptance of online opinions in online communities. This study by Cheung et al. (2008) only found relevance and comprehensiveness to significantly influence information usefulness amongst all the items of the variable argument quality affecting consumers' decisions to adopt information in the online communities.

In addition, many researchers have added new variables tailored explicitly for the environment to enrich the original IAM model (Wang, 2016). For example, Zhu et al. (2016) created a study model and incorporated variables to evaluate the impact of C2C communication on online community users' purchase decisions. Furthermore, Zhu et al. (2016) discovered that argument quality, source legitimacy, and tie strength all had a

positive relationship with product usefulness rating and, as a result, influenced purchase decisions.

Similarly, by incorporating perceived travel risk into the IAM model, Tseng and Wang (2016) explored how perceived risk affects users' information processes on travel websites. Furthermore, Tseng and Wang's (2016) findings revealed that argument quality and source reliability impacted consumers' intentions to accept knowledge via perceived utility. The authors also reported that perceived risk directly affected intentions to adopt information while perceived usefulness indirectly affected intentions to adopt information.

Some researchers replaced the original mediated variables of the IAM with new ones to build complex models. For example, Cheung, Luo, Sia and Chen (2009) added more variables. The study concluded that the three informational determinants, including other variables, affected eWOM review adoption.

Similarly, Jin, Cheung, Lee and Chen (2009) used IAM and user satisfaction theories to construct a model to study how social networks encouraged members to use the information inside the network. Their research found that information quality and source reliability, directly and indirectly, affect information use and continuation intention.

Meanwhile, Li (2013) investigated the impact of persuasive messages on information system adoption by including the social influence theory in the IAM model. This study found that two elements of persuasive communication, source legitimacy and argument quality, were shown to impact social influence emotional reaction and cognitive response substantially. The authors also confirmed the interconnection between emotive, cognitive, and behaviour. Moreover, this result confirms the moderating role of international social influence on cognitive response and behaviour intention.

Concurring, Chen, Chen and Hsu (2011) combined IAM with three new variables: confirmation with previous belief, suggestion consistency, and message trustworthiness. Chen et al. (2011) model also looked at how consumers used eWOM in online groups.

Additionally, Chen et al. (2011) model analysed how consumers adopted eWOM in online communities. Their studies revealed that information usefulness and adoption were influenced by both message and source reliability.

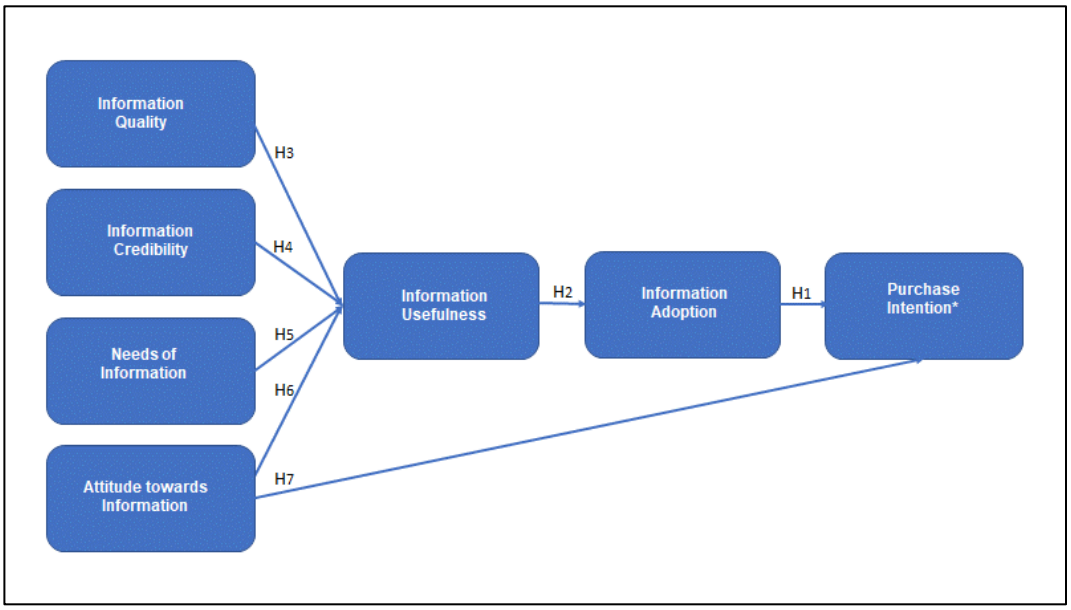
The study also found that message quality, source credibility, previous belief confirmation, and suggestion consistency all substantially impacted message credibility and that message credibility influenced information uptake directly.

Some researchers integrated IAM and TRA models in their studies to understand customer behaviours towards information (Wang, 2016). For example, Gunawan and Huarng (2015) devised a model incorporating IAM, TRA, perceived risk, and social interactions to emphasise the importance of understanding viral marketing impacts on consumers' purchase intent via social networks and media.

The study's findings revealed that user opinions regarding information usefulness were influenced by source trustworthiness and social influence. Furthermore, this research discovered that source credibility and social impact influenced behavioural intentions linked to subjective standards. Perceived risk had a detrimental impact on behaviour intention as well.

Erkan and Evans (2016) consistently evaluated the impact of (eWOM) via social media on customers' purchasing intentions. In this work, Erkan and Evans (2016) combined the Information Acceptance Model (IAM) with the TRA model's relevant components to create the Information Acceptance Model (IACM). Figure 4.4 depicts how information qualities, in combination with customer behaviour, impact purchase intentions. This study's findings showed that eWOM information qualities and consumer behaviour had a beneficial influence on customers' purchase intentions.

Figure 4.4 Information Acceptance Model



Source: (Erkan and Evans, 2016, p.50)

As such, six hypothesised relationships between the variables of the IACM found statistical significance except for attitudes towards information which was influential on information usefulness resulting in the not hypotheses supported.

As a result, the IACM provides a complete approach by including consumer behaviour and information characteristics into the same model (Erkan & Evans, 2016). In essence, the IACM broadens the definition of information adoption by integrating consumer behaviour in describing how behaviour intentions are influenced.

This present study integrates the related components of the IACM to measure hypothesised relationships amongst the variables of this study's research model. In this research, a variable named information accuracy is integrated with a mediated variable, as the study needs information to improve the study's effectiveness and give more valuable and practical conclusions and implications (See Figure 4.6 hereunder).

4.2.3 Competitive Intelligence Embeddedness Model

Nowadays, digital technologies and big data facilitate internal and external information (Trabucchi & Buganza, 2020). Consequently, the increased availability of internal and external information leads to a networked digital economy for organisations to grow and compete in the ecosystem (Cavallo, Ghezzi, Sanasi & Rangone, 2019; Subramaniam, Iyer & Venkatraman, 2019).

As these events happen, they present more information, thus leading to a variety of opportunities and threats for leaders to select quality information for better decision-making (Artusi & Bellini, 2020). Organisations with strong business analytics capabilities have also been experiencing an upsurge in performance growth (Zikopoulos, Deroos & Parasuraman, 2013).

CI acquire and decode competitor information to capture opportunities in the competitive environment (Tuan, 2015, p. 212). Organisations should gather CI to strengthen their competitive advantage and sustainable growth during unprecedented times (Du Plessis & Gulwa, 2016). The significance of CI goes beyond developing a competitive advantage and greatly enhances an organisation's long-term sustainability (Cavallo et al., 2019).

Therefore, organisations need cutting-edge analytical capabilities and use CI now more than ever (Iansiti & Euchner, 2018; Itani, Agnihotri & Dingus, 2017). CI and the understanding of competitive forces have been widely used in today's highly business environment (Agnihotri & Rapp, 2011; Benny, 2013; Halt, Donch, Stiles & Robert, 2014).

Since the market landscape is getting more competitive daily, organisations are confronted with larger volumes of competitive information and new competitors contesting for customers and attention. Thus, organisations are becoming harder to get ahead and stay ahead in an ever-changing business landscape (Crayon, 2019, p.4).

For that reason, CI deals with dynamic market activities, thereby positioning organisations to take advantage of competitive insights and opportunities (Crayon, 2019). This view highlights the significance of CI in reinventing processes and practices for handling new

data sources, analysis frameworks, and stakeholder demands in the dynamic business environment (Crayon, 2019).

Essentially, CI process capability sorts relevant information for decision-making and develops a competitive advantage for organisations (Rouach & Santi, 2001). Recent research by Cavallo et al. (2020) found a correlation with CI practices throughout the strategy formulation process. The study's results suggested that CI practices are widely adopted for tactical use besides their strategic relevance and diffusion.

This means that embedding CI throughout the organisation is a business imperative. It requires leadership attention and awareness across the organisation (Wright et al., 2008a). In addition, leaders should foster an organisational culture that embeds CI activities to ensure that they are supported and used throughout the organisation (Saayman et al., 2008).

Leadership engagement, therefore, authenticates the importance and implementation of CI processes and a supportive organisational culture, thus contributing to the successful utilisation of CI throughout the organisation (Ardito & Petruzzelli, 2017). This view signifies that leadership engagement alongside culture and structure that encourages trust and aiding communication and the flow of information ensures the implementation of CI activities throughout the organisation (Nasri, 2011).

Considering that CIE is based on intra-organisation information, leaders should embrace quality information so that CI is successfully integrated into the corporate culture (Markovich et al., 2019).

Furthermore, Markovich et al. (2019) submit that leadership commitment is needed to embed processes and procedures that support CI activities to enhance CIE capabilities through the organisation's value chain. CIE relies on the use of information to create and add value that improves customer satisfaction (Markovich et al., 2019, p.715).

Currently, the web-based sources of competitive information have influenced the collection and analysis of information through the CI cycle (Ferrara, De Meo, Fiumara & Baumgartner, 2014).

With that, the development of a CIE capability advances the implementation of the CI cycle through the organisation. CIE likewise integrates information for knowledge creation to improve performance (Moustaghfir, 2009).

CI Web competitive data has gained some traction over the past twenty years (Du Toit, 2015; He et al., 2015). Du Toit (2003), Rouach and Santi (2001), and Vaughan and You (2011) contend that most of these studies concerted on web data collection techniques without evaluating the effect of data utilisation on the CI-related organisational culture (Markovich et al., 2019). According to Rakthin, Calantone and Wang (2016), the organisation's ability to acquire, assimilate, transform and apply knowledge strongly predicts its culture and performance.

This view indicates that information quality positively impacts organisational performance (Yoo, 2014); while some existing research studies, as pointed out by Dabrowski (2018, p. 115), have still primarily ignored the value of quality information in the era of the information society. The growth in volumes of information imposes the development of processes to filter and avoid information overflow (Markovich et al., 2019).

In balancing costs related to screening information, organisations need to evaluate benefits arising from using Web CI to source quality information (Işık et al., 2013). This view shows that the internet positively impacts information quality, further influencing organisational efficiency and performance (Raghunathan, 1999; Teo & Choo, 2001).

Some studies found that web information quality significantly affected organisational capabilities and performance (Setia, Setia, Venkatesh & Joglekar, 2013). Inevitably, web development has created a platform for competitive information sources externally to organisations, thereby improving accessibility and availability of intelligent information to enrich CI (Leeflang, Verhoef, Dahlström & Freundt, 2014; Reinmoeller & Ansari, 2016; Sher & Lee, 2004). However, Gilad (2015b, p.4) maintains that organisations should pay more attention to information usage rather than collecting competitive information and producing intelligence to improve decision-making quality.

Consequently, web information sources augment the CIE capability function and provide decision support to enhance organisational performance (Markovich et al., 2019). CIE capability, therefore, inspires CI-related organisational culture and performance. CIE also dispenses competitive information about the organisation's external environment to make effective strategic and tactical decisions (Markovich et al., 2019). Indeed, CI is critical to collecting and distributing information and developing and formulating business strategies.

Therefore, CI quantifies and qualifies the organisation's strategy (Amiri et al., 2017; Bartes, 2014; Calof & Wright, 2008; Maritz & Du Toit, 2018; Sewdass & Du Toit, 2014; Vidigal, 2013). Apart from the gathering and dissemination of information, CI is a strategic management tool that scans and analyses trends in the market to fast-track effective decision-making processes in organisations (Amiri et al., 2017; Du Toit, 2013; Franco et al., 2011; Pellissier & Kruger, 2011; Sewdass & Du Toit, 2014).

With increased competition, limited resources and increased uncertainty in the current business environment, these factors are challenging for leaders of organisations to improve performance and deal with the changing competitive landscape (Waithaka et al., 2016). Organisations, therefore, need to identify factors that can enhance productivity to accelerate organisational performance (Akram & Waheed, 2012).

In coping with challenges organisations face, most organisations must use information adequately to improve their performance and productivity (Aramide & Adebisi, 2018). Therefore, CI plays a vital role in identifying, developing, and sustaining resources and capabilities that create a competitive advantage for organisations and enhance performance and strategy development processes (Waithaka, 2016).

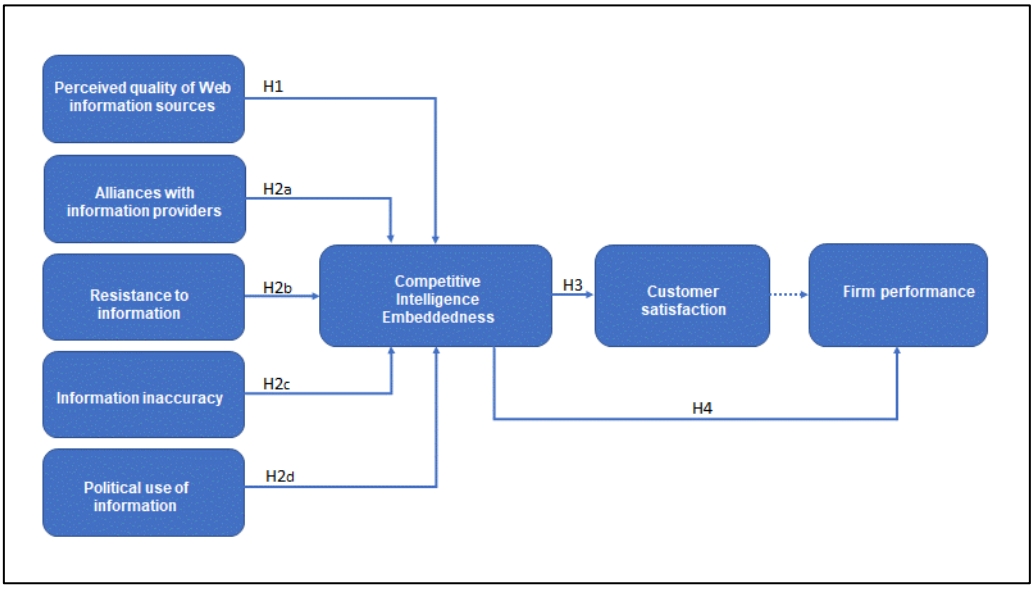
Furthermore, Waithaka (2016) reiterates that CI practices contribute significantly to on-ongoing activities and the organisation's performance. He mentions that CI practices proactively manage emerging opportunities and risks for organisations to increase their performance and gain a competitive advantage. In essence, CI practices enable organisations to develop, implement and monitor strategies that create and protect

shareholders' value long-term, thereby attaining sustained competitive advantage for the firm (Protiviti, 2012).

Previous research studies like ones from Akram and Waheed (2012), Mariadoss, Milewicz, Lee and Sahaym (2014), Rapp et al. (2015), Sepahvand et al. (2016), Tahmasebifard and Wright (2018), and Uzoamaka et al. (2017) have found the existence of causative relationships between CI and organisational performance. These studies have, however, not explored CIE capabilities in understanding the association between customer satisfaction and the organisation's overall performance.

For that reason, Markovich et al. (2019) developed a research model that integrated CIE with related information attributes, customer satisfaction and organisational performance (See Figure 4.5 below).

Figure 4.5: CIE Research Model



Source: (Markovich et al., 2019, p.719)

In this research, Markovich et al. (2019) explored the drivers of CIE and its impact on Web information sources. The hypothetical relationships between the variables of this study were tested using the SEM. The study's results showed that CIE positively correlated with the perceived quality of web information sources and partnerships with information providers.

In addition, the results found a positive effect on CIE and customer satisfaction, with no direct effect between CIE and performance. The research model by Markovich et al. (2019) demonstrates that CI's influence on performance depends on improved customer satisfaction, whereas improved customer satisfaction impacts the overall performance.

This result signifies that a well-established CIE capability within an organisation augments customer satisfaction. An improved customer experience inspires organisational performance (Markovich et al., 2019). Organisations that continually scan the environment according to a plan detect opportunities and threats on time and respond to the dynamic business environment (Garcia-Alsina et al., 2016, p.60). CI is a proactive technique used by an organisation to analyse and monitor the environment in pursuit of formulating marketing strategies that aid its competitive position in the markets in which it operates (Ahmed et al., 2014, p.343).

In essence, CI screens the environment and provides intelligent information about competitors' actions and customers to improve the organisation's competitive position by putting customers at the centre of the organisation's activities (Hughes, Le Bon & Rapp, 2013). In this study, the influence of CIE on information attributes, organisational capabilities, the environment and organisational performance is examined by adopting related components of (Markovich et al., 2019) research model to measure hypothesised relationships amongst the variables of this study's research model (See Figure 4.6 hereunder).

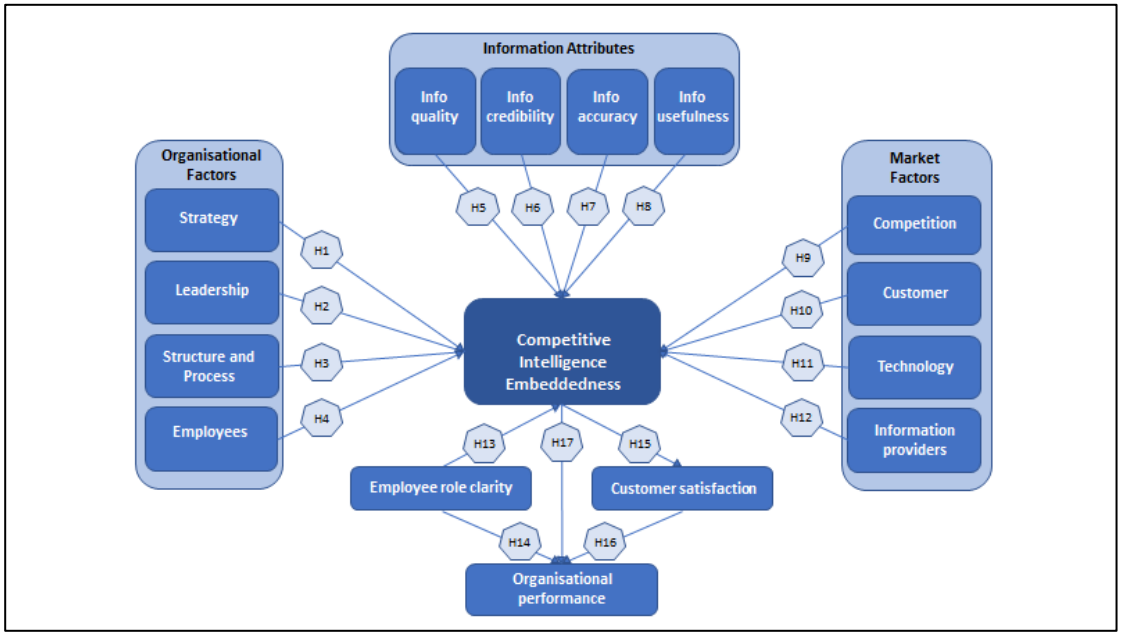
This research model links the variable named employee role clarity with customer satisfaction and organisational performance from the original model to improve the mediated effect of CIE through employee role clarity on organisational performance and customer satisfaction.

4.3 Conceptual Framework and Research Hypothesis

This section proposes a conceptual framework to organise and direct this study based on the discussion and extensive literature review. This study's integrated research model incorporates related components of the CIE by Markovich et al. (2019), IAM by Erkan and Evans (2016), and the TOE framework by Duh and Fabiao (2018) to develop an integrated CI strategy model for the life assurance industry in SA.

Given the varying context, this study's integrated model introduces different variables with additional constructs to enrich this study's proposed research model. The conceptual model used in this work is depicted in Figure 4.6, which specifies the hypothetical connections between components.

Figure 4.6: The Proposed Conceptual Framework



Source: Author's compilation

The conceptual framework in Figure 4.6 above shows that the independent variable is employee's role clarity, information attributes, organisational and market factors, and their related items, while organisational performance is the dependent variable for this study.

Meanwhile, the mediating variable is CIE, while customer satisfaction is the moderating variable. Based on this conceptual framework, the researcher develops the research hypothesis for this study.

4.3.1 Hypothesised Relationships Between Constructs in the Conceptual Model

This research introduces new variables influencing the hypothetical relationships amongst this study's different constructs. This section covers the hypothetical relationships of this study's independent, confounding, dependent, mediating and moderating variables.

4.3.2 Organisational Factors

The organisational dimensions relate to various factors influencing organisations, namely a company's centralisation, formalisation, technology readiness, the complexity of the company's management structure, organisational readiness, and the capacity of the organisation to innovate as well as top leadership support (Angeles, 2014; Brender & Markov, 2013; Chang et al., 2013; Lin & Chen, 2012; Oliveira et al., 2014; Sila & Dobni, 2012).

In addition, Duh and Fabiao (2018) state that the quality and characteristics of the company's resources, employees, and informal and formal communication between employees, among others, are important organisational dimensions. Riyadh et al. (2009, p.215) contend that the organisational context consists of resources (capital and human), organisational scope, and size.

Infrastructure, relevant systems and technical skills augment organisational readiness (Zhu & Kraemer, 2005). Consequently, organisations will improve their performance only if they can deploy their tangible and intangible resources to attain competitive advantage (Grant, 1991).

Essentially, organisations that link their capabilities with the mastery of markets and customers are renowned for being market-driven. Inevitably, market-driven organisations understand customer needs and acquire competitor knowledge (Day, 1994, p.37). In this research, capabilities include leadership, employees, strategy, structure and process.

According to Riyadh et al. (2009, p.223), organisational capabilities deliver organisations' competitive advantage. This view indicates that organisational capabilities are a company's internal strengths, and they command how an organisation attains superior performance and competitive advantage absolute to the competition (Barney, 1991; Penrose & Penrose, 2009).

Organisational capabilities that have more attention improve the relationship between organisational resources and performance (Obeidat, Abdallah, Aqqad, Akhoershiedah & Maqableh, 2016; Rehman, Mohamed & Ayoup, 2018; Shurafa & Mohamed, 2016).

Because of compelling globalisation, organisations are looking for strategies to compete more successfully on a global scale. In this way, organisations may flourish in a growing global complicated business environment by reviewing their outmoded business models, antiquated leadership techniques, and traditional thinking (Castelli, 2016, p. 217).

Leadership today is no different than it was years ago; leaders are currently overwhelmed by the increasing demands imposed by globalisation and adjusting to the new effective ways of work (Castelli, 2016). As society is becoming more reliant on technology, leaders are beholden to embrace the power of digital technologies to create an organisational culture that is transparent, relevant, meaningful, engaging, and inspiring in the workplace environment (Sheninger, 2014).

Meanwhile, the wealth of information continues to grow. Leaders' knowledge increases in tandem, thus probing them to arrange internal organisational processes to facilitate change in response to changes dictated by the external environment (Cekuls, 2015b).

According to Garrett Jr and Neubaum (2013), top leadership support relates to commitments and sponsorship from the highest-ranking executives for projects and strategy implementation.

Salaheldin's (2009) study found that leadership, top management support, and organisational culture positively impacted overall performance. This implies that leadership is a process of influencing people and guiding them to achieve organisational goals (Hogan, Curphy, Kaiser & Premuzic, 2018; Northouse, 2019).

Concurring with this view, Chemers (1997) describes leadership as a process of social influence wherein people collaborate and support each other to accomplish a common task. Ivan (2015) contends yet that leadership is the capacity to influence people's behaviour without using any force to achieve business objectives.

While doing so, leaders influence the processes that determine and improve teams and the organisation (Yukl, 2012, p.457). Leaders balance and implement organisational changes and maintain the human aspects of changes that affect organisational performance (Cekuls, 2015b).

Notably, preceding research studies have established significant relations between leadership and performance (Agle, Nagarajan, Sonnenfeld & Srinivasan, 2006; As-Sadeq & Khoury, 2006; Ling, Simsek, Lubatkin & Veiga, 2008; Lo, Ramayah, Min & Songan, 2010; Waldman, Javidan & Varella, 2004).

While effective leadership is essential because it determines the success or failures of organisations, leaders must be equipped with information about competitors' performance and analyse it to attain the best results for organisations to thrive in the dynamic environment (Ivan, 2015).

On occasion, leaders have failed to comprehend what change involves in adapting to the changing business environment characterised by the complexity of decision-making and responding quickly to unfavourable market conditions (Stanford, 2016).

Leaders, therefore, need appropriate skills and values to play an important role in affecting organisational changes. Likewise, De La Robertie (2016) found that top management support influenced the environment, knowledge management, protected intangible assets, and scanned the environment.

In contrast, Chinyamurindi (2016) found that middle management communicates information gathered from CI to top managers to assist them in making strategic decisions. This result shows that CI is used at various levels in the organisation's value chain and departments, regardless of position (Asri & Mohsin, 2020). Leaders must elaborate fundamental measures within the organisation to effectively implement potential changes (Cekuls, 2015b). Implementing changes requires employees to change their habitual behaviours to embrace the organisation's CI system.

The way CI and information are disseminated within the organisation then depends on the organisational culture, employee involvement, and buy-in in collecting and exchanging business information (Cekuls, 2015b). In essence, leaders must persuade employees to accept change based on the mutual trust they have earned from those they have asked to change (Cekuls, 2015b). Moreover, top management should have the willingness and financial resources to employ and support skilled employees to ensure the adoption and desire to use various technological innovations within organisations (Angeles, 2013).

Top management support is, therefore, crucial for ensuring that employees' capabilities, such as lack of skills and technical knowledge, getting addressed to avoid delays in adopting technology and innovation within the organisation (Ahmadi, Ibrahim & Nelashi, 2015).

With CI providing analytical and predictive information to simplify decision-making, leaders are armed with accurate contextual information to respond proactively and guide teams towards success (Ivan, 2015). Nonetheless, an organisation's success depends on the collaboration of employees at all stages of the technological process of CI. Thus, leaders need to define the requirements and goals for CI that determines the focus and the scope of information needs within the organisation (Cekuls, 2015b).

Leaders should also create a CI-specific function with formal structures and processes that support the entire organisation. This intelligence function will anticipate and interpret the drivers of change for organisations to rapidly adapt and implement their concrete plans in the evolving complex business environment (Arcos, 2016).

Inevitably, the intelligent function will interpret changes that inform organisations' management decisions and actions to achieve greater strategic agility in the dynamic business environment (Arcos, 2016).

With strategy integral in providing direction and setting goals for organisations, the CI's specific function will contribute to the tactical formulation of strategy. Furthermore, it will focus primarily on strategy implementation, monitoring and performance for leaders to make informed decisions (Cavallo et al., 2020). The CI function will ensure that strategic practices are employed and resources allocated appropriately to steer the company in the right direction and set in processes to monitor and control the organisation's strategic outcomes (Jarzabkowski, 2003).

Equally, CI supports the strategic processes in organisations, thereby providing top management with insights about the state of the organisational competitiveness relative to its operational environment to respond swiftly to the changing conditions (Havenga & Botha, 2003).

Du Plessis and Gulwa (2016) found that decision-makers valued CI's contribution to strategy development. Similarly, Cavallo et al. (2020) found significance between CI practices and strategy formulation processes. The foundation of CI is based on factual information gathered in the present form, and it forms an integral part of the daily operation of an organisation. This view shows that CI practices are adopted for tactical use rather than strategic relevance and diffusion (Cavallo et al., 2020).

In essence, CI arms leaders with strategic intelligence to assist them in assessing competitors' strategies and formulating strategies to counter the competition (Ahmed et al., 2014). Therefore, leaders' attention and awareness are vital to establishing CI throughout the organisation (Wright et al., 2008a). The following hypotheses are formulated from these discussions and presented below.

- H1: Strategy contributes positively to competitive intelligence embeddedness.
- H2: Leadership commitment and support has a positive influence on competitive intelligence embeddedness.

- H3: Structure and process has a positive influence on competitive intelligence embeddedness.

- H4: Employee capability leads to competitive intelligence embeddedness.

4.3.3 Information Attributes

Today, information is used much more than traditional historical analysis due to organisations becoming more reliant on information to respond swiftly to customers and competitor actions (Alshikhi & Abdullah, 2018). Organisations use competitor information for tactical and strategic decision-making to create a competitive advantage (Aramide & Adebisi, 2018)

According to Opoku (2015, p.62), information is the most sought-after resource in the world since it is needed to solve complex problems and make decisions that affect both the present and the future. Consequently, access to immediate information globally assists organisations in collecting, analysing, and disseminating information relating to changes in competitors' actions, customer needs, and technological developments (Ghasemaghaei, Hassanein & Turel, 2017).

Data and information quality play a significant role in developing and creating competitive advantage (Howard, Lubbe & Klopper, 2011). Furthermore, Howard et al. (2011,p.291) suggest that information quality determines how knowledge or intelligence is communicated.

According to Diakopoulos and Essa (2008), information quality is made up of objectivity and subjectivity elements of accuracy, reliability, credibility, comprehensiveness and transparency. Accuracy guarantees that the version of events presented is verifiable from multiple reliable sources (Diakopoulos & Essa, 2008).

Furthermore, Diakopoulos and Essa (2008) contend that reliability reports on the dependability and consistency of information. On the other hand, credibility depends on reliability through trustworthiness and is a perceived subjective quality of an information source or object.

Equally, perceived knowledge, skill and experience are important attributes of credibility (Diakopoulos & Essa, 2008). In essence, information is an important competitive resource for organisations due to the critical role played by quality information in the current knowledge-intensive business environment (Zhu, Madnick, Lee & Wang, 2014).

Organisations must gather, monitor, and analyse user-generated data and their rivals' social media sites, including blogs, Facebook, and Twitter, to listen to and comprehend what consumers are saying about the competition to gain a competitive edge (He et al., 2015).

Nowadays, almost all internet users generate eWOM information, so the quality and credibility of that information have never been more important (Xu, 2014). Concurring, Tseng and Wang (2016) found that the source's quality and credibility affect consumers' intentions to adopt information and use it. Similarly, Jin et al. (2009) found that information quality and source credibility affect information usefulness and continuance intention directly and through satisfaction indirectly.

In contrast, Gunawan and Huarng's (2015) results showed that credibility influenced information users' attitudes toward its usefulness. Equally, Erkan and Evans (2016) found that information quality and credibility affected the usefulness of the information. In essence, information is of good quality if it comes from a trusted source and can be used to connect and exchange ideas (Mai, 2013). Therefore, information quality is an important characteristic of information management.

For instance, it determines the quality of information developed and produced within the organisation (Azemi, Zaidi & Hussin, 2017, p.429). Aramide and Adebisi (2018) have also identified that adequate use of information assists organisations in coping with challenges, enhancing companies' productivity and performance.

Gorla, Somers and Wong (2010) reported that information quality positively impacted organisational performance, while perceived quality and innovativeness were found (Yoo, 2014). Setia et al. (2013) also found a direct relationship between web information quality and organisational capabilities and performance.

Additionally, previous research found that information used by decision-makers impacted organisational performance (Souchon, Diamantopoulos, Hulzmüller, Axinn, Sinkula, Simmet & Durden, 2003).

With a rapid increase in data collection, the high quality of information produced improves decision-making processes and inspires competitive advantage for organisations (Azemi et al., 2017). Inevitably, most organisations depend on web information sources because of their accessibility and relevance (Fleisher, 2008; Wong & Saunders, 2020).

Ho (2008) similarly found that the perceived quality of web competitive information sources and management's action-orientated use of that information impacted the organisation's CIE capabilities and performance. Therefore, the availability of quality information plays a significant role in the success of organisations (Hartono, Li, Na & Simpson, 2010).

Consequently, the abundance of quality information has glimmered organisations to develop their analytical capabilities and maintain an internal unit dedicated to analysing, collecting, and disseminating web information (Markovich et al., 2019). Most businesses have also created formal structures and processes to accommodate CI-specific functions (Crayon, 2019; Reinmoeller & Ansari, 2016).

In addition, these organisations can manage quality information successfully and continue to gain a competitive advantage in the knowledge-intensive business environment (Azemi et al., 2017). Moreover, Azemi et al. (2017) advocate that increased data collection and storage in organisations have given rise to quality information.

Therefore, organisations have increasingly invested in technology that collects, stores, and processes big data (Zhu et al., 2014). Organisations have also considered employing big data analytics to improve their products and services and make intelligent decisions (Ashrafi & Ravasan, 2018; Ghasemaghaei et al., 2017). Big data and its analytical methods analyse data to obtain intelligent information about markets for organisations to make effective decisions, increase their market share, and stay ahead of the competition (Maroufkhani, Wagner, Wan Ismail, Baroto & Nourani, 2019).

Data analytics tools provide organisations with the intelligence to respond quickly and improve their efficiencies and agility to adapt to changes in the market (Roberts & Grover, 2012).

With knowledge of competitor information stimulating business performance, organisations should establish an integrated and intelligent system that analyses and collects competitor activities (Aramide & Adebisi, 2018). Organisations use web search engines and web crawlers to collect data and other tools that can analyse data (He et al., 2015).

CI is an integrated and intelligent system that analyses, collects, and disseminates competitor information to augment the organisation's strategic and tactical decision-making process (Aramide & Adebisi, 2018). CI also permits an organisation to identify its competitor's strengths and weaknesses to improve its strategic decisions against its competitors (Bose, 2008; Teo & Choo, 2001). From these discussions, the following hypothesis were articulated:

- H5: Quality of competitive information has a positive impact on competitive intelligence embeddedness.
- H6: Credibility of competitive information has a positive impact on competitive intelligence embeddedness.
- H7: Accuracy of competitive information has a positive impact on competitive intelligence embeddedness.
- H8: Usefulness of competitive information has a positive impact on competitive intelligence embeddedness.

4.3.4 Market Factors

An organisation's macro-environment comprises wide-ranging stakeholders: industry members, customers, competitors, suppliers, and communities (Angeles, 2014, p. 97).

This view is congruent with McGonagle and Misner-Elias's (2016) view that the competitive environment comprises the organisation's competitors, customers, suppliers, and regulatory and political environment.

The macro-environment also includes the availability or absence of technology service providers (Gutierrez et al., 2015). Essentially, the macro-environment consists of external forces that shape and dictate how the industry is forced to develop (Duh & Fabiao, 2018). Organisations that understand competitor dynamics and are forewarned by these activities will respond rapidly to the market dynamics (Tuan, 2016).

The macro-environment focuses on organisations that prioritise external factors that influence the industry and how these factors impact the business operations (Salwani et al., 2009). In that way, these external forces influence the innovation needs of organisations and their abilities to acquire the resources and the actual deployment of technological innovation (Angeles, 2014).

Moreover, Angeles (2013) indicates further that these external forces could shape how organisations adopt innovative strategies and prioritise resources to pursue innovation and its implementation. Corroborating this view, Porter (1980) found that organisations that had capabilities to attract customers and defend themselves against the competitive forces had leading-edge and enjoyed a competitive advantage relative to the industry.

Today's business environment requires organisations to be knowledgeable about the competitive environment to succeed. Organisations that have the agility to fit with the environmental context then scan this environment in search of the most effective ways of anticipating threats and opportunities to sustain competitive advantage (Zhang et al., 2012).

With globalisation increasing organisations' competitive environment, technological advances, social and economic changes as well, and a shortening product life cycle have taken centre stage, thus leading to hyper-competition (Mutua & Ngugi, 2012). Indeed, organisations operating globally must bear competitive pressures from customers, services, and suppliers to cope with the disruptions created by unstable environments (Du Toit, 2003; Maritz & Du Toit, 2018). To compete effectively in the globalised environment, organisations yearn for advanced competencies that provide accurate and timely information on opportunities and threats and competitor analysis supporting the entire organisation's strategic planning processes (Waithaka, 2016).

The survival of organisations in the global environment depends mainly on the strategic role CI plays in establishing a highly well-designed, accurate and rigorous strategy for companies to stay ahead of their competitors (Dahou, Hacini & Bendiabdellah, 2012, p.47).

This is because CI provides information about competitors' present and future behaviours, customers, technologies, governments, markets, and the general business environment (Yap et al., 2013b). CI gathers relevant information from the competitive environment to be used explicitly for planning and decision-making (Kotler et al., 2019).

CI comprehends all the information in the organisation and permits the creation, spread and transmission of knowledge from markets and investors (Chevallier et al., 2016). CI particularly aids organisations with a tactical, operational, and strategic analysis of the markets, competitors, and industries to find a fit between the organisation and its environment (Dahou et al., 2012, p. 47). Furthermore, Dahou et al. (2012) mention that CI provides much-needed information about opportunities and threats that await to confront the organisations compared to the industry.

CI also gathers accurate and relevant information about the organisation's competition, customers, and suppliers to anticipate market developments and respond proactively. Nazar and Seidali Route (2017) found that knowledge of trends in the market and foreknowledge of competition, technology and strategy had a positive and significant relationship with organisational flexibility. Similarly, Asghari, Targholi, Kazemi, Shahriyari and Rajabion (2020) found that competitor information influenced CI significantly.

In anticipating transitions to the industry structure, Gilad (2016,p.18) points out that technology changes can be disruptions attributed to the use of new technology by rivals, suppliers, and customers. For instance, the internet raised customers' bargaining power more than ever before. The technology positions of an organisation may determine its competitive advantage and innovation opportunities, and the set of technologies the organisation has mastered informs innovation and CI (Sarica, Yan, Bulato, Jaipurkar & Luo, 2019, p.127). This view shows that information technology can improve the

sustainability of organisations in a highly competitive global business environment (Wu, Straub & Liang, 2015).

As globalisation and the rapid advancements of Information and Communications Technologies (ICTs) continue to increase competitive pressure significantly, customers' and suppliers' business interactions produce large quantities of information that require technological advances to perform data analytics (Chang et al., 2014a).

A study by Urbinati, Bogers, Chiesa and Frattini (2019) found that exchanging big data and analysts was essential for co-innovation with suppliers and customers. Organisations should therefore adopt the extensive use of ICTs in business processes to collaborate effectively with customers and suppliers globally (Abhari et al., 2017).

Implementing ICTs would require technology vendors to facilitate the acquisition and the use of technological innovation (Duh & Fabiao, 2018, p.18). Using technology vendors enables efficiency in adopting technology across the organisation (Ahmadi et al., 2015).

In providing support and enablement of roles to ensure IT competencies, Chakravarty et al. (2013) suggest that leaders should account for a myriad of contingencies when assessing the effects of IT competencies on organisational agility and its performance.

Furthermore, Chakravarty et al. (2013,p.976) state that organisations should eliminate constraints when assessing competencies by considering the capabilities needed for selecting and acquiring IT infrastructure and its configuration to ensure that IT is implemented effectively within the organisation.

Ismail and Ali (2013) also found that support from technology vendors assisted organisations by lessening and mitigating the lack of internal technical expertise and skills. Customer demands can also influence organisations to adapt to their needs and preferences (Angeles, 2013).

Therefore, organisations must adjust the high technology solutions to customers’ benefits to achieve organisational performance (Lo et al., 2016). For instance, Ghobakhloo et al.

(2011) found that customers' pressure was the main cause of IT adoption within organisations.

As such, technology adoption encourages communication, delivers customer service, and helps organisations maintain and improve their level of performance (Ozuem, Howell & Lancaster, 2019).

Equally, technology adoption assists with data analytics that can educate customers on solutions and competitors in preventing the churn of customers (Crayon, 2019). In addition, Asghari et al. (2020) found that information technology significantly and positively influenced CI. This result indicates that if CI is deployed successfully in the organisation, it will provide executives with knowledge for making decisions that will ensure organisations sustain competitive advantage in the macro-environment (Ahmad, 2015).

With competitor information becoming more critical for every organisation's tactical and strategic decision-making process, CI processes use a variety of competitors' information sources to obtain intelligent information (Gračanin et al., 2015). Furthermore, Gračanin et al. (2015) stress that information can be obtained from internal and external sources, including formal and informal sources. For instance, employees acquire a valuable source of competitive information through customer interactions.

Additionally, employees get information from the actions of competitors (García, Macià & Salvador, 2009; Gračanin et al., 2015). This view shows that CI programs do not provide information services. Corporate libraries, research vendors, and web-based aggregators of information outsourced collectors offer information services to organisations (Gilad, 2016). The core responsibility of information providers is to provide answers to specific questions. In comparison, the role of CI is to interpret information and provide management with a perspective on risks and opportunities (Gilad, 2016).

Tanev and Bailetti (2008) found that specialised suppliers had the highest rate of using information about customers and the industry compared to new technology-based and service firms. From these discussions, the following hypothesis were articulated:

- H9: Competitor information is positively influenced by competitive intelligence embeddedness.

- H10: Customer insights is positively influenced by competitive intelligence embeddedness.

- H11: Technology readiness is positively influenced by competitive intelligence embeddedness.

- H12: The organisation's enduring relationship with information providers is positively related to competitive intelligence embeddedness.

4.3.5 Employee Role Clarity

Business performance has become an important global focus for management and leadership (Azam, Haseeb & Samsudin, 2016). Organisations are thereby required to do more than usual to sustain in the long run due to the intensity of the global competition (Haseeb, Hassan & Azam, 2017).

For organisations to succeed in this highly intense global business environment, they depend on the high performance of their employees and meet their objectives. Undoubtedly, employees greatest need to perform at high levels for organisations to achieve their strategic goals and maintain their competitive advantage (Andrew, 2017).

Organisations should shape the attitudes and behaviours of employees for responsive business performance (Fisher, McPhail & Menghetti, 2010). Bolumole, Grawe and Daugherty (2016) found that when employees are given more autonomy in their job function and increased clarity in their roles, they are willing to become more responsive to customer needs. This result is consistent with Ahmed, Khalid, Ammar and Shah's (2017) conclusion that work discretion correlates with business performance.

Therefore, leaders must develop a compelling vision for the organisation and define employee roles that positively impact teams' success (Lynn & Kalay, 2015). Furthermore,

Lynn and Kalay (2015) found that clarity of the organisation's vision positively affected team performance.

In contrast, support for the organisation's vision and role clarity was not significantly related to team performance (Lynn & Kalay, 2015). According to Kauppila (2014, p.738), role ambiguity arises when employees are uncertain about their expectations. Role ambiguity is a bottleneck affecting the team's effectiveness, while role conflict creates work-related stress for employees and impacts productivity (Thangavelu & Sudhahar, 2017).

Notably, ambiguity inhibits the ability of employees to perform their duties effectively, impacting organisations negatively (Bolumole et al., 2016). Importantly, role clarity refers to how employees understand what is expected from their roles to achieve their duties, tasks, and objectives to deliver on organisational outcomes (Hinkin & Schriesheim, 2008).

Chan and Schmitt (2000) posit that role clarity relates to the information available for employees to perform their tasks effectively. Role clarity is essential, assisting employees in attaining expected performance outcomes (Sangkala, Ahmed & Pahi, 2016). It is imperative to provide employees with clarity regarding what they are required to do, how to do it, and articulating the organisation's goals (Newman, Allen & Miao, 2015).

Consequently, role clarity assists employees with shaping their behaviour in their roles for more responsive outcomes (Sangkala et al., 2016). Essentially, leaders should clarify roles by ensuring that roles support employees with cognitive structures that define how they will achieve their goals (Yukl & Mahsud, 2010).

Hassan (2013) contends that role clarification involves guiding and coordinating employee work-related activities by setting task objectives for the team. Role clarity was particularly found to mediate the relationship between organisational socialisation tactics and self-rated task performance (Lapointe, Vandenberghe & Boudrias, 2014). Therefore, leaders must clearly articulate their employees' roles and responsibilities regarding what

will be expected from them and how they will be evaluated to ensure organisations achieve their goals and performance (Thangavelu & Sudhahar, 2017).

This view shows that employees with clear roles are more likely to subscribe to the organisation and its goals. Previous research studies have proved that role clarity positively impacted both performance and satisfaction (See for example, Bolino & Turnley, 2005; Martins, Gilson & Maynard, 2004; Moynihan & Pandey, 2007; Podsakoff, Mackenzie, Paine & Bachrach, 2000; Salamon & Deutsch, 2006).

In addition, Thangavelu and Sudhahar (2017) found that performance feedback and role clarity enhances employee satisfaction and performance. Consequently, organisations that do not provide job clarity to their employees lag and often produce poor performance results (Nansubuga & Munene, 2013).

Some studies have highlighted that lack of job clarity does not correlate with work outcomes and hinders the organisation's performance prospects (Mukherjee & Malhotra, 2006; Shepherd, Fowler, MCCormick, Wilson & Morgan, 2016). Hassan (2013 found that offices with a high degree of role definition had considerably greater levels of job satisfaction and reduced rates of worker turnover.

Overall clarity in the offices moderated the effects of role clarification on work satisfaction and turnover behaviour. It means that committed employees develop a bond with their organisation, inspiring organisational performance (Andrew, 2017, p.2). Also, Andrew (2017) confirmed a strong relationship between three independent commitment variables and organisational performance.

Another important aspect is employee engagement, which contributes significantly to employee well-being and performance outcomes (Azam et al.,2016; Abidin, Haseeb & Islam, 2016).

Engaged employees tend to express and invest their physical and mental capabilities to accomplish performance outcomes (Markos & Sridevi, 2010). In addition, employee engagement adds value to individual and organisational performance outcomes.

Equally, Dalal, Baysinger, Brummel and LeBreton (2012) found that employee engagement and job performance were overall predictors of employee performance; while Akin, Shuck and Reio Jr (2014) found employee engagement at work moderating different job factors and organisational outcomes.

With the widespread adoption and use of the internet, knowledge improves productivity, innovation, and economic benefits for organisations (Fombad, 2015). Leaders must therefore influence employees' attitudes and behaviours to ensure that they are aligned to organisational goals and provide them with direction to carry out their duties successfully (King & Grace, 2005). Gathering intelligence requires appropriate policies, formal structure, and procedures for employees to contribute effectively to the intelligence system and benefit from knowledge from the intelligence process (Dishman & Calof, 2008, p.769).

CI is the integration of information throughout the organisation, enabling employees to provide the information required to gather market intelligence (Calof, 2017b). Employees may make more accurate strategic decisions by implementing CI activities, which improves organisational performance and competitiveness (Ferrier, 2001).

Employee job clarity and identification with organisational values have been shown to contribute to transmitting brand-related information critical to employee success (King & Grace, 2010). Better employee engagement, internal knowledge, and formal infrastructure improve CI procedures and inspire CI performance (Saayman et al., 2008).

Meanwhile, successful organisations have embedded CI as a formal function in their operation (Du Toit, 2015, p.16). This centralised CI unit is equipped with specific CI personnel performing CI practices and procedures. Doing so contributes to organisational performance (Calof, 2017a). From these discussions, the following hypotheses were tested:

- H13: Employee role clarity positively influences organisational performance.
- H14: Employee role clarity positively influences competitive intelligence embeddedness.

4.3.6 Competitive Intelligence Embeddedness, Customer Satisfaction and Organisational Performance

In the current business environment, organisations are overwhelmed by rapid cultural, political, and technological developments (Sepahvand et al., 2016,p.1280). Leaders experience challenges with change management and the complexity of the organisation's interaction with the turbulent external marketing environment (Igbaekemen, 2014, p.17).

There is an inevitability for organisations to achieve sustainable growth and create value, and prompt intelligence to succeed globally (Boikanyo, Lotriet & Buys, 2016). Based on that need, organisations must stay abreast of these changes and make suitable decisions that will minimise the impact of risk and safeguard their survival in turbulent times (Salguero & Quintero, 2016, p. 136).

With the rapid evolution in competitive markets creating additional pressures, organisations are compelled to adapt quickly, survive, and remain flexible to manage unpredictable ecosystems (Nazar & Seidali Route, 2017). On the other hand, organisations that adapt and update their plans based on a constant flow of information will be alerted about changes in the environment faster than their competitors (Tahmasebifard & Wright, 2018). Igbaekemen (2014) posits that reliable data and information provide analytic and predictive capabilities for effective strategic management decisions.

Today, business executives rely on social media to collect customer reviews and produce the knowledge needed to enhance organisational performance (He, Shen, Tian, Li, Akula, Yan & Tao, 2015a). As profit maximisation is derived from existing organisational capabilities, leaders need to engage employees now more than ever to ensure that profits are maximised in the long run (Kortmann, Gelhard, Zimmermann & Piller, 2014).

Therefore, organisations need to integrate their dynamic capabilities to ensure better coordination of resources to inspire organisational performance (Nazar & Seidali Route, 2017). According to Rakthin et al. (2016,p.1), technological and market knowledge are among the most resources organisations can use to attain a competitive advantage.

Importantly, organisations have to obtain timeously accurate, reliable, and relevant information from internal and external sources to anticipate and identify potential problems before they arise, along with analysing the information to prevent and find solutions to these problems (Igbaekemen, 2014).

Organisations with superior market knowledge perform better than their rivals (Rakthin et al., 2016). Subramanian and IsHak (1998) also found that organisations that employ advanced competitor analysis systems to monitor market trends exhibited significant profitability. In essence, organisations use precise information and knowledge about the environment to make operational, tactical, and strategic decisions (Shujahat et al., 2017).

In that way, organisations use knowledge to remain competitive and strengthen their relationships with customers and employees (Singh & Samalia, 2014). Most organisations have purposely improved their efficiencies using advanced technologies, skilled labour, and best practices to survive and prosper in the modern world (Osborne & Hammound, 2017).

Inevitably, organisations need to gather intelligence about customers, competitors, and markets to prosper in the dynamic and unpredictable business world and ensure their success in the long-term (Hamad & Yozgat, 2017). Organisations should thus compare their performance against competitors. In doing so, they should strengthen their capabilities by improving the intelligence poised in the modern world (Parvizi & Seyadat, 2014). CI particularly equips organisations with comparative analytics permitting them to benchmark performance against their peers (Bose, 2008; Sanderson, 2013).

Organisations need to entrench CI processes to facilitate access to intelligent information for decision-makers (Salquero & Quintero, 2016). CI is also a process that discovers, analyses, and converts information collected from the external environment into organisational knowledge (Singh et al., 2012; Kim, Dwivedi, Zhang & Jeong, 2016).

Moreover, the involvement of key employees based on their skills, experience, and their level of management is crucial in the CI process since they are familiar with operating

instruments such as competitor and trend analysis to determine the drivers that influence organisational performance (Opait, Bleoju, Nistor & Capatina, 2016).

CI identifies new market opportunities to create value and improve organisational performance (Salguero et al., 2019). In so doing, CI examines capabilities, intentions, actions, and competitors' vulnerabilities for organisations to anticipate any developments in the market quicker than the competition (Uzoamaka et al., 2017a).

This view conforms with Onifade, Thiery, Osofisan and Duffing (2013), who uphold that CI provides insights into competitor actions and intentions. In addition, CI provides insights about customers, competitors, markets, and regulators for leaders to identify new opportunities and forecast changes required for organisations to achieve sustainable competitive advantage (Calof et al., 2018). Uzoamaka et al. (2017a) has shown that CI significantly influenced market share and that customer intelligence positively affected quality service delivery.

Tahmasebifard and Wright (2018) likewise found that CI positively affected market performance and had the greatest among subtypes investigated. Similarly, Akram and Waheed (2012), Sepahvand et al. (2016), and Waithaka (2016) found a positively and statistically significant effect on organisational performance. Waithaka et al. (2016) showed that target-orientated CI positively and statistically connected with performance.

Mohsin et al. (2015) also found that CI positively correlated to innovative performance. In contrast, Asri and Mohsin's (2020) study deduced a relationship between CI practices and organisational performance. Magasa, Mphahlele and Awosejo (2014), and Stefanikova et al. (2015) found that implementing and utilising CI enhance performance and affect an organisation's sustainable growth.

Rapp et al. (2015) research indicated a support relationship between Individual Competitive Intelligence (ICI) use and performance. Furthermore, the study concluded that organisations should create an environment that facilitates the collection and use of ICI since it positively impacts individual performance. Organisations need to recognise

customer needs, competitive actions, and market trends. In doing so, they should identify and develop capabilities necessary for long-term performance (Day, 1994).

Such an expanded capability should acquire information through multiple channels and integrate the customer's voice into every aspect of the organisation's activities (Kumar, Jones, Venkatesan & Leone, 2011). Moreover, CI is a capability that fosters a positive customer experience at every stage of the customer journey (Hughes et al., 2013).

This view signifies the role played by leadership in ensuring that CI processes are embedded to distribute and share knowledge about the company's customers and competition to improve customer satisfaction and organisational performance (Rouach & Santi, 2001). Markovich et al. (2019, p.711) define customer satisfaction as "an evaluation of the customer's overall purchase and consumption experience with the firm over time".

According to Mazreku (2015, p.28), customer satisfaction is a perceived value experienced through a relationship between the customer, products and services, and the company that provides products and services. Customer satisfaction is achieved through services that meet customers' unique demands, resulting in customer loyalty (Hill, Jones & Schilling, 2014). Customer satisfaction is about creating value for consumers through providing quality service to encourage future intentions (Sohaib, Akram & Ur Rehman, 2016, p. 106).

Equally, customer satisfaction is derived through pre- and post- purchases of products and services (Mazreku, 2015). Customer satisfaction is, therefore, a vital metric that organisations use to measure the retention of existing customers (Morgan & Hunt, 1994).

Organisations that build close relationships with their customers over time experience high customer satisfaction (Anderson & Yu, 2016). In essence, higher levels of customer satisfaction enhance customer retention, purchase intention, and the organisation's probability. It encourages existing customers and promotes new customers on behalf of the organisation (Neupane, 2014). Therefore, satisfaction enhances customer loyalty and the company's profitability (Sohaib et al., 2016).

Curtis, Abratt, Dion and Rhoades (2011) similarly found that increased customer satisfaction, repurchase rates, and loyalty of customers positively influenced organisational performance and led organisations to attain competitive advantage.

Sohaib et al. (2016) found a positive relationship between satisfaction and repurchase intentions, trust and commitment. This result shows that higher customer ratings are the best indicators of an organisation's future profit (Mazreku, 2015). Organisations that fail to satisfy customers will not prosper and endure into the future (Odunlami, Olawepo & Emmanuel, 2013).

Anderson and Yu (2016) corroborate this by stating that cost stickiness was greater in companies with higher customer satisfaction. Customers create value for organisations, so customer satisfaction is vital to a company's performance (Gomez, McLaughlin & Wittink, 2004).

Organisations, therefore, need to focus on the degree to which they satisfy their customers. Product consumption results in customer satisfaction, enhancing the company's profitability (Odunlami et al., 2013). Furthermore, Odunlami et al. (2013) contend that organisations should create customer satisfaction from both new and existing customers to increase sales outcomes and profitability.

Banker and Mashruwala (2007) found that customer satisfaction affected the company's future performance. Similarly, Anderson, Fornell and Mazvancheryl (2004) found a favourable implication between customer satisfaction and shareholder value.

In addition, Van der Wiele, Boselie and Hesselink (2002) found that customer satisfaction influenced different matrices of business performance, for instance, market share, profit margin, total sales, interested party value and total revenues.

Customer service is a strong predictor of further business performance measured in yearly sales growth, net operating cash flows, yearly sales growth, and market share (Kristensen, Martensen & Grønholdt, 2002). Yet, Neupane's (2014) research showed a weak positive relationship between customer satisfaction and business performance. In contrast, Odunlami et al. (2013) recorded a positive association between customer

satisfaction and revenue growth, concluding that the satisfaction of customers enhances productivity.

CI inspires customer satisfaction, sequentially enhancing the organisation's profitability (Afolabi & Adegoke, 2014). Hughes et al. (2013) also demonstrated value in gathering and using CI at the tactical level for customer interface. Notably, CI objectives, quality of intelligence, and delivery of intelligence on time are the critical drivers for overall customer satisfaction (Kruger, 2003).

Given that CI scans the environment and obtains market information for organisations to improve their competitive position, a well-established CIE first enhances customer satisfaction and organisational performance (Markovich et al., 2019, p.715).

Organisations must embed processes and procedures and build relationships with information providers to establish and strengthen their CIE capability (Markovich et al., 2019). In essence, CIE processes convert raw data into usable information to add value for customers and improve their experience and satisfaction with the organisation’s products and services. In so doing, CIE enhances the overall performance of the organisation.

Ahearne et al. (2013), and Hughes et al. (2013) found that CI had a significant effect on marketing performance along with overall organisational performance measured by growth, turnover, positioning, and expectations performance matrices (Johns & Van Doren, 2010).

In addition, Markovich et al. (2019) found that organisations improve their performance by creating CIE through enhanced customer satisfaction. The authors further reported that CIE did not directly influence organisational performance, but it mediated performance through customer satisfaction.

Also, Markovich et al. (2019) indicated that CI’s influence on performance was subsequent to improving customer satisfaction levels, which sequentially impacts performance. In effect, CI stimulates customer satisfaction, which enhances the

organisation's profitability (Afolabi & Adegoke, 2014). The following hypotheses were articulated:

- H15: Competitive intelligence embeddedness positively influences customer satisfaction.
- H16: Customer satisfaction positively influences organisational performance.
- H17: Competitive intelligence embeddedness positively influences organisational performance.

4.4 Conclusion

While research studies have established a link between CI and organisational performance, it was found that explicit strategies produced CI and, in turn, led to successful performance (Jenser & Søilen, 2013). CI also strengthens the strategic planning process by facilitating competitive strategies' effective implementation (Arrigo, 2016; Cavallo et al., 2020).

Moreover, CI units within organisations seem to focus more on customer value analysis to understand clients' needs in specific markets (Cavallo et al., 2020). An integrative framework that combines a CI-related capability and information attributes, organisation and market factors that drive performance are necessary for effective strategy implementation.

This present study has introduced an integrated conceptual model aligned with research objectives. The literature review aided in the formation of hypothetical linkages between the constructs in this conceptual framework. The research approach utilised to gather data and test the conceptual model for this study is described in the next chapter.

Chapter Five: Research Methodology

5.1 Introduction

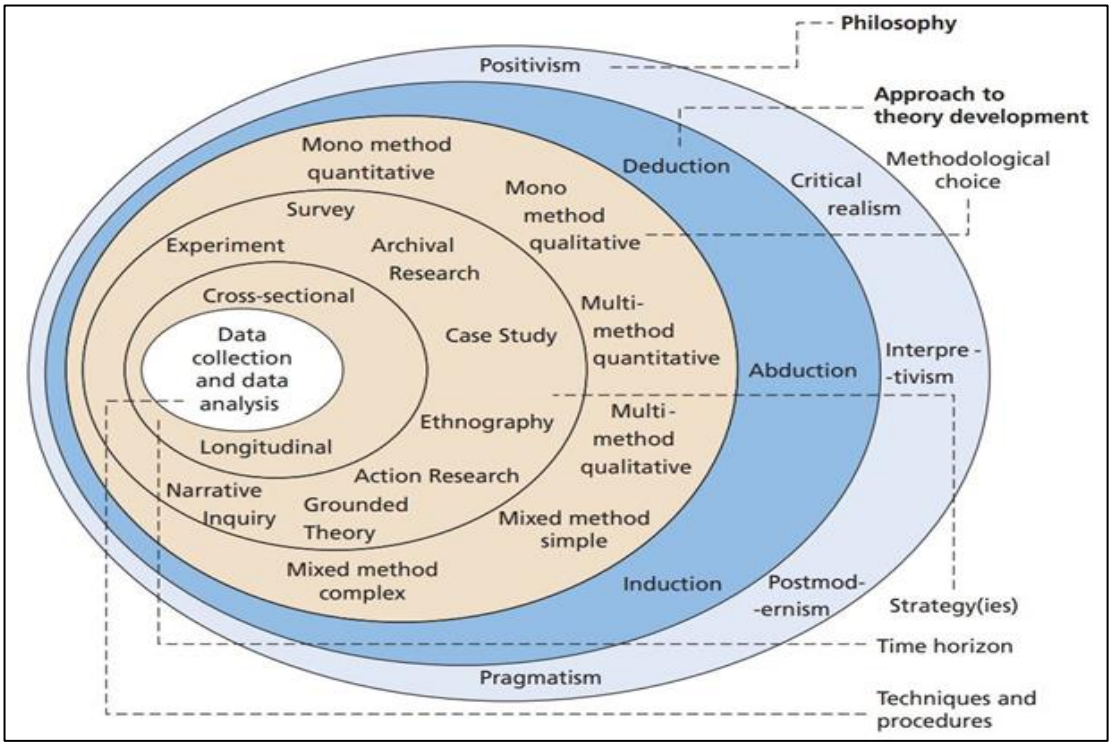
The preceding chapter discussed theories, and models of the TOE Framework, IAM, IACM, and CIE. The review of relevant theoretical models was conducted in the previous chapter. The conceptual model that organises and directs this research was presented. Furthermore, theoretical relationships between constructs that helped formulate hypotheses for the study were discussed and evaluated empirically.

This chapter outlines the research process and method used to achieve the research objectives and examines the relationships between variables. Furthermore, the research approach, research design, data-gathering tools, sample population, size, and method, as well as ethical considerations and issues of reliability and validity, are reviewed.

5.2 Research Process

An onion represents a research process whereby its several layers must be followed consistently when research is carried out Saunders et al. (2019, p.128). Figure 5.1 illustrates the research onion's layers depicted by (Saunders et al., 2019).

Figure 5.1: The Research Onion

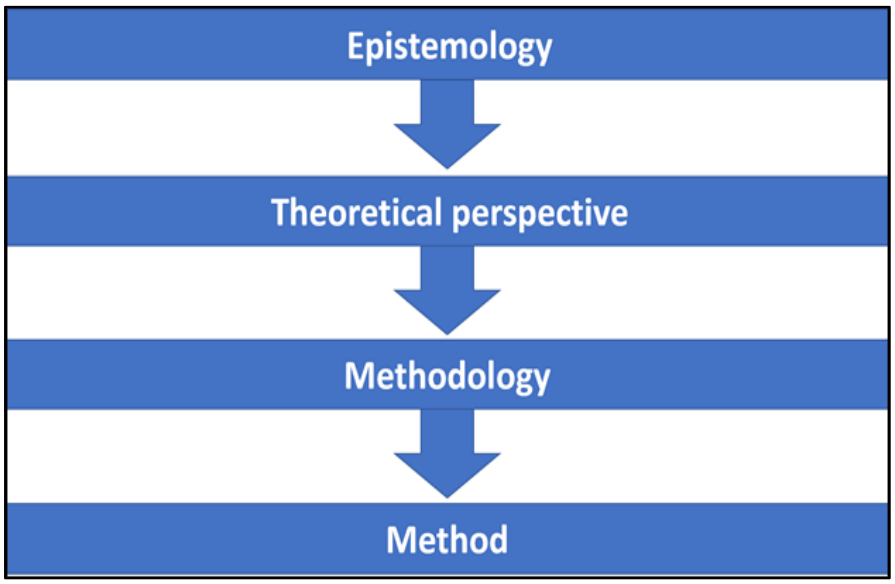


Source: (Saunders et al., 2019, p.130)

Saunders et al. (2007) classify positivism and subjectivism as philosophies in their research onion. The classification made by Crotty's (1998) research stages in Figure 5.2 clarified the distinction between epistemology and theoretical perspectives.

This calls attention to Crotty's (1998) framework in Figure 5.2 below, thus suggesting that epistemology is a fundamental part of the researcher conducting a study that connects to the theoretical perspective the researcher is applying in the study. The theoretical perspective has implications for which methodologies would be suitable in a research study. The method associated with the research methodology is selected according to the study's theoretical philosophy.

Figure 5.2: A Research Framework



Source: (Crotty, 1998, p.4)

This study followed the guidelines of the research onion modelled by Saunders et al. (2019), and Crotty's (1998) research framework. The classification of Crotty's (1998) research process was found helpful in justifying the researcher's decision in selecting a philosophy to be applied, a 'theoretical perspectives', methodology, and methods since they are related to each other. The following sections detail the critical steps adhered to in this research.

5.3 Research Paradigm

Choosing an appropriate research philosophy for a research endeavour is the first step in the research process (Newby, 2014, p.35). According to Saunders, Lewis, and Thornhill (2016, p.107), a research philosophy is an umbrella phrase relating to knowledge production and its nature.

A research philosophy refers to developing knowledge in a particular field (Simpson, 2009). In essence, research paradigms point researchers in the right direction to reflect their primary theories concerning the world and the foundation of knowledge (Guba & Lincoln, 1994).

Therefore, a research paradigm is the first layer of the research onion and is crucial in conducting a study (Zefeiti & Mohamad, 2015, p.2). According to Levin (1988), a research paradigm is a belief or an idea about collecting, interpreting, and analysing data collected.

A research paradigm is also an outline that needs to be followed during the study. Neuman (2011, p.94) describes a paradigm as “a whole system of thinking”. Moreover, a paradigm refers to the established research practices in a particular discipline (Mouton, 1996, p.203). Similarly, Collis and Hussey (2013, p.59) opine that a paradigm is more than just a philosophical framework since it guides how research is carried out.

Precisely, a paradigm includes a body of research and methodologies, and it could be a context for observation and understanding (Babbie, 2020, p.32; Creswell & Poth, 2016, p. 18; Rubin & Babbie, 2010, p.15). Paradigms are thus a set of fundamental beliefs about the nature of reality, what we may know about this reality and how knowledge about this reality will be produced (Gringeri, Barusch & Cambron, 2013).

Therefore, ontology and epistemology are two main research paradigms (Kalof, Dan & Dietz, 2008; Saunders et al., 2015). Ontology is a philosophical perspective on how one experiences reality. On the other hand, epistemology sees knowledge-producing, comprehending, and using as legitimate and acceptable (Wahyuni, 2012).

Wahyuni (2012, p. 69) affirms that axiology and methodology are two fundamental beliefs that affect how reality is investigated. Furthermore, Wahyuni (2012) believes that axiology deals with ethics and the role of values in the research and the researcher’s attitude concerning the subject studies, while methodology refers to a model for undertaking a research process in a particular paradigm.

Notably, research paradigms relate to the nature of knowledge and the development of that knowledge (Wahyuni, 2012). Therefore, researchers must state paradigms that guide their research work and a process depicting how knowledge will be produced (Lincoln & Guba, 2013). Paradigms influence research methods, data gathering instruments as well as how the results of the study are construed (Gringeri et al., 2013).

The roots of qualitative and quantitative research methods may be traced back to various philosophical research paradigms such as positivism and post-positivism (Creswell, 2009, pp, .6-6; Denzin & Lincoln, 2011, p.1; Gratton & Jones, 2014, pp. 23-26). Interpretivism and critical theory are the two main sub-paradigms of post-positivism.

While realism bridges positivism and post-positivism (6 & Bellamy, 2011, p.60); this quantitative research is deductive and scientific; therefore, a non-experimental research design was employed to answer the research question. Scientific methods use different approaches to generate quantitative data and search for predictions to generalise findings (Shah & Al-Bargi, 2013).

The positivist paradigm is a scientific method, and it is associated with quantitative methods (Makombe, 2017). Furthermore, Makombe (2017) states that the relationship between the positivism paradigm and quantitative research methods is identical and robust.

As quantitative methods generate numerical data, large quantities of data were orderly organised to discover new patterns and establish causative relationships amongst the study's variables. Descriptive statistics were employed to create meaning from quantitative data and identify common themes in the respondents' answers to the closed-ended questionnaires (Rehman & Alharthi, 2016).

This study mixed ontology, epistemology and axiology as acceptable approaches to understanding social phenomena (Wahyuni, 2012, p.71). This research employed the positivist paradigm that combines epistemology and methodology philosophies. The positivist methodology explained causal relationships and patterns among the study's variables.

The epistemology of the positivist paradigm ensures the objectivity and independence of the object investigated (Shah & Al-Bargi,2013). According to Shah and Al-Bargi (2013), a positivist methodology is concerned with explaining relationships from patterns and trends derived from answering the research question.

Positivist methodology relies on systematic experiments. This research used statistical analysis to establish the hypothetical relationships among this study's constructs. The extraneous variables were controlled to assure validity and generalisability of the findings (Shah & Al-Bargi, 2013).

Additionally, probability sampling was employed to select participants for this study. In differentiating between people and objects, a random sample was used to define the nature of the population, and it offered respondents an equal chance of inclusion in the study (Shah & Al-Bargi, 2013).

5.4 Research Approach

Saunders et al.'s (2019) research onion is divided into abductive and deductive (See Figure 5.1). Saunders et al. (2019, p.144), state that abductive methods involve in-depth historical studies of pre-existing structures, using various methods and data types that suit the subject matter.

In contrast, deductive methods involve highly structured, large samples, measurement, and quantitative methods, providing a range of data analysis. As opposed to the deductive approach, inductive approaches employ qualitative methods of analysis that allow for a wide range of interpretations (Saunders et al., 2019, p.144). Hence, research approaches or strategies should be seen as related to the actual research methods yet, distinct from them simultaneously (Greener, 2008).

Researchers use research approaches to gather data, and they may use specific instruments such as a self-completed questionnaire or structured interviews (Bryman & Bell, 2015). There are two fundamental approaches to a research project that scholars in every discipline should decide on which method to use before undertaking research (Yilmaz, 2013).

These major approaches to research are quantitative and qualitative (Creswell & Creswell, 2017; Yilmaz, 2013). In a quantitative approach, a researcher should have the know-how to obtain comprehensive findings which are presentable concisely (Yilmaz, 2013).

The quantitative approach involves data organisation in the quantitative form; this can then be assessed through intensive formal and rigid analysis. In contrast, the qualitative approach to research involves subjective assessment of attitudes, opinions, and behaviours (Kothari, 2004).

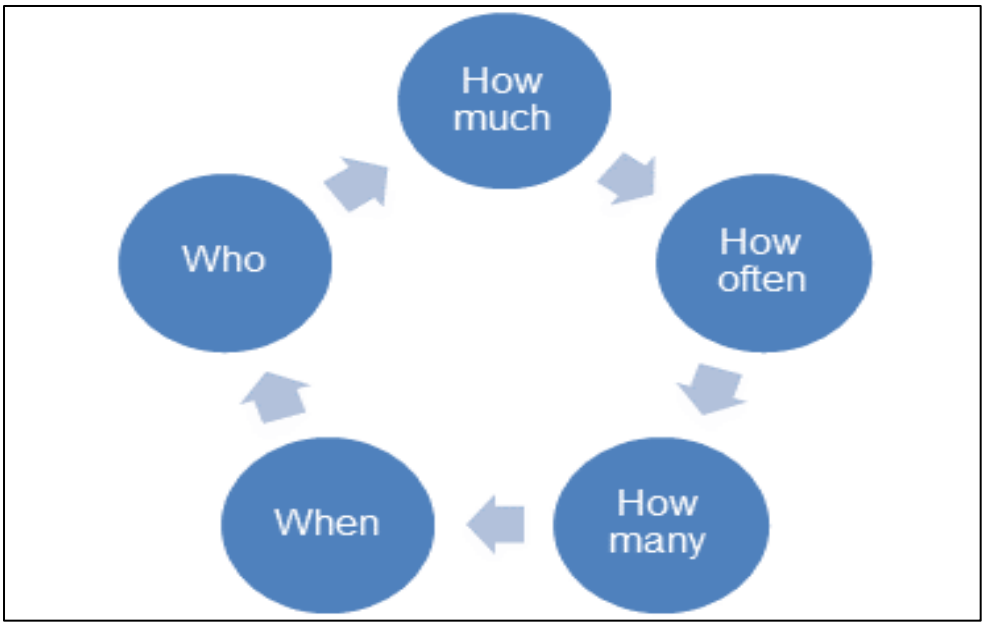
Greener (2008, p. 17), however, states that “a qualitative approach to research is likely to be associated with an inductive approach to generating theory, often using an interpretivist model allowing the existence of multiple subjective perspectives and constructing knowledge rather than seeking to find it in reality”.

The positivist approach utilises the hypothetical-deductive approach toward phenomena and hypotheses. It depends on generalizable empirical studies based on observations and hypotheses tests (Babbie, 2020). This study used the positivist research paradigm to support quantitative methodology (Antwi & Hamza, 2015).

The positivist paradigm permitted the researcher to employ scientific methods to produce knowledge for this study. The researcher used the positivist paradigm to discover critical theory for this study (See, for example, Rahi, 2017; Thanh & Thanh, 2015).

Quantitative research is an approach that tests theories objectively by probing relationships among variables (Babbie, 2020). This approach answers questions about how much, how often, when, and who (Cooper & Schindler, 2008). These questions follow a systematic process depicted in Figure 5.3 hereunder.

Figure 5.3: Systematic Process of How Questions Aare Answered



Source: Authors' compilation

Quantitative research is related to a deductive approach to testing the theory by narrowing it down into more specific verifiable hypotheses (Antwi & Hamza, 2015; Khaldi, 2017). This deductive orientation study focuses on theory testing. This research adopted theory for developing and testing hypotheses in a specific research context.

In this research, cause and effect narrowed the theory to specific variables, hypotheses, and questions. The quantitative approach tested the theory by probing the relationships among variables (Creswell & Creswell, 2017). The research approach for this study was quantitative, and a survey instrument was employed for data collection. The quantitative approach was selected due to its objectivity and coherence in solving the research problem for this study.

The quantitative approach is flexible, and it enhanced the validity and reliability of research findings (Babin & Zikmund, 2016). Significantly, quantitative approaches assisted the researcher in choosing the correct sampling technique, research instrument and how data for this study were analysed and discussed.

As such, the researcher was also able to quantify the data, which enhanced the accuracy of the research findings. Statistical analysis and standardised measures are used in quantitative studies, and data about the phenomenon is collected and analysed systematically (Hammarberg, Kirkman & de Lacey, 2016).

This research used statistics to test causative relationships between variables and the hypotheses of this study (Khaldi, 2017). Meanwhile, detailed statistical analysis enhanced the accuracy of results, thus assisting the researcher in uncovering and establishing relationship patterns, trends, and correlations between various variables.

5.5 Research Design

A research design is a master plan the researcher uses to answer a research question. It articulates the methods and procedures used to collect and analyse research data (Van Wyk, 2012; Zikmund, Carr, Babin & Griffin, 2013). A research design then sets out the overall framework of a study and maps the plan to gather and analyse data (Panneerselvam, 2014).

Sekaran and Bougie (2016, p.95) define a research design as “the blueprint for the collection, measurement, and analysis of data, based on the study's research question”. Equally, Saunders et al. (2015) explain a research design as a general plan for answering research questions. Furthermore, Saunders et al. (2015) contend that a research design is classified into three broad categories depending on how much control the researcher maintains while conducting the research.

Cooper and Schindler (2014) hold that a research design articulates the structure of the research problem, the context, organisation, or the pattern of the relationship among variables of a study and the strategy of the exploration used to obtain empirical evidence.

According to Mertens (2014), and Panneerselvam (2014), a research design provides a road map for a study. It gives details of all steps to be followed to ensure the quality and accuracy of research (Cohen, Manion & Morrison, 2017). Therefore, a research design provides the researcher with an overall strategy to collect and analyse data and answer the research question to reach an outcome (Walliman, 2017).

Furthermore, it provides a general structure for solving a research problem (Leedy & Ormrod, 2016). However, Bryman and Bell (2015, p.60) mention that the research design and data collection directions depend on a specific research question from hypothetical concerns.

Different research objectives and methods often lead to varying types of research designs (Walliman, 2017; Zikmund et al., 2013). According to Scott and Garner (2013), quantitative research design assists the researcher in drawing meaningful conclusions based on statistical measurements of the variables under study. This study is deductive; therefore, quantitative research methods and descriptive design was employed.

This quantitative research design is non-experimental, so the researcher did not manipulate the variables of this study, but the researcher only observed and interpreted data about events that occurred in the present (Khaldi, 2017). This study involves more variables; therefore, a descriptive research design was employed to address the research question for this study, its aims, and objectives.

Cross-sectional and longitudinal studies are the two types of descriptive research. A cross-sectional design involves collecting data from sample units at one point in time (Aggarwal & Ranganathan, 2019). This study follows a cross-sectional design since it involves collecting information on the presence of more variables of interest at a specific point in time (Aggarwal & Ranganathan, 2019).

This descriptive research design supported the researcher in designing and conducting large sample field surveys (McNabb, 2015). Descriptive research seeks to acquire information about the current status of phenomena to predict an event that is likely to happen again under the same circumstances (Walliman, 2017).

Methods also involved range from a survey depicting the current situation through a correlation study investigating the relationship between variables to developmental studies determining changes over time (Cooper & Schindler, 2008). The descriptive survey method was used to search for complexity beyond factual information obtained from the characteristics of the whole sample (Salaria, 2012).

Data collection methods for descriptive research include surveys, interviews, observations, and portfolios. The online survey was used to collect primary data for this project. Surveys allowed open-ended responses and led to an in-depth study of individual cases.

5.6 Research Methodology

A research methodology is a step-by-step approach to solving the research problem. It may articulate a science of studying how research is carried out scientifically (Kothari, 2004). According to Henning, Van Rensburg and Smit (2004, p. 36), a research methodology involves the value of the study to society, why it should be done, and what it is, including how researchers conduct their research projects and the techniques by which research is conducted determines the specific tools used in a research project (Leedy & Ormrod, 2016).

Thus, a research methodology refers to a model of research within a particular paradigm, constituting the underlying beliefs that guide a researcher to focus on one set of methods over another (Wahyuni, 2012, p.72). Sarantakos (2013) nonetheless stresses that a research method is theoretic and independent of methodologies and paradigms.

Wahyuni (2012, p.72) argues that a research method consists of specific procedures, tools, and techniques used to collect and analyse data. Generally, research methods involve data collection tools, such as self-completion questionnaires and structured interview schedules (Bryman & Bell, 2015).

Punch (2003) believes that selecting an appropriate research method for the study depends on its research questions, objectives, and topic. The researcher must employ suitable methods to achieve the research objectives and goals. Qualitative research is often confirmatory and collects and tests surveys, interviews, focus groups, conversational analysis, and observation (Olds, Moskal & Miller, 2005).

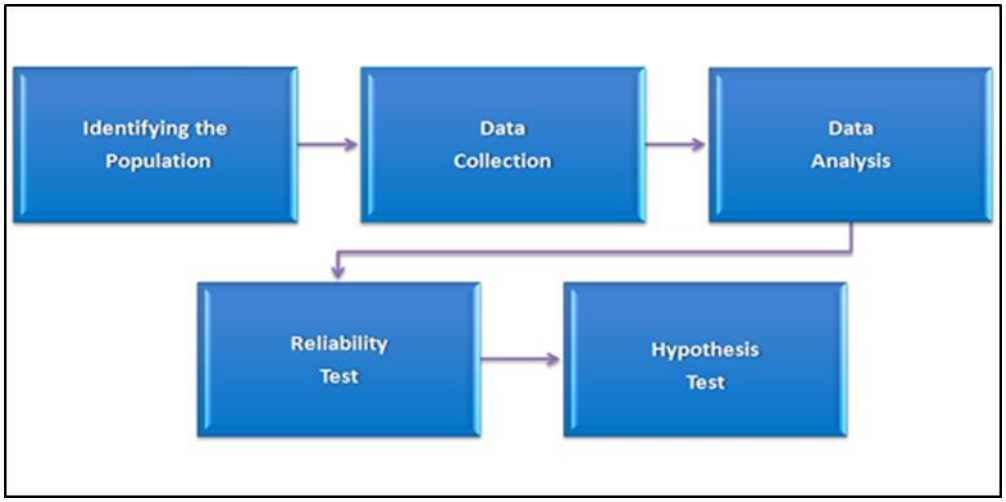
According to Creswell (2009), qualitative research involves eliciting the views, attitudes, and perceptions of interviewees regarding an issue related to their work. In contrast,

quantitative research methods collect and analyse data that is structured and represented numerically.

Quantitative research is, therefore, very effective, as it answers the “what” and “how” of the research problem (Goertzen, 2017). A quantitative design may include and describe the categories of data to be gathered, sampling and recruiting tactics, data collecting protocols, and data management and analysis procedures, in addition to the sample size (Zefeiti & Mohamad, 2015, p.4).

For this purpose, this study follows five methodological stages depicted in Figure 5.3 below. This research illustrated methodological steps in Figure 5.4 that took place systematically to attain the research objectives. This reaffirms that a research methodology is an approach the researcher brings to acquire information (McNabb, 2015, p.12).

Figure 5.4: Methodological stages of the research process



Source: Synthesised by Author

A quantitative method is a scientific method, and its traits are akin to the positivist research paradigm (See, for example, Antwi & Hamza, 2015; Rahi, 2017). This study tested the theory by collecting primary data from respondents.

The research findings were analysed based on empirical evidence generated from various statistical tests (Rahi, 2017). Quantitative research is deductive, so hypotheses are confirmed and tested with specific data. The quantitative research methods use systematic, standardised approaches to produce quantitative data to answer research questions (Rudestam & Newton, 2014).

Quantitative research is appropriate when the relationship between variables is measured (Robson, 2002). The quantitative method investigated the hypothetical relationships between different constructs in this study. The researcher used statistics to test causal relationships amongst the variables of this study. The variables of this study were represented numerically as the rate of recurrence whose causative relationships were explored by applying statistical techniques.

Cost, time, and logistical limitations make an electronic survey preferable. The online survey method collected primary data for this research. The survey strategy used is associated with the deductive approach. In business and management research, a survey strategy is commonly used; therefore, a survey strategy was used to answer who, what, where, how much and how many (Saunders et al., 2015).

Managerial research can cover reporting, explanatory, descriptive, and predictive studies (Cooper & Schindler, 2014). This descriptive study was designed to describe the distribution and collection of information from one or more variables of interest (Aggarwal & Ranganathan, 2019). The cross-sectional descriptive survey was selected as it is the most appropriate option as it was conducted at a particular point in time.

Such a survey provided the researcher with speedy, less-expensive, efficient and accurate information about the population (Zikmund, 2003, p.175). Surveys allowed the researcher for open-ended responses, making it easy for the researcher to compare, generalise and summarise the results they produce.

Survey research can obtain a large sample while maintaining respondents' anonymity (Zikmund, 2003). It offers respondents convenience and low administration costs and provided flexibility in survey design (Zikmund, 2003).

In this study, all participants completed the online surveys at their convenience and leisure time. The research instrument was an e-mailed structured and self-administered questionnaire.

A set of eighty-four closed-ended questions were posed to the respondents comprising questionnaire items of this study variable, namely, competitive intelligence embeddedness, customer satisfaction, employee role clarity, information attributes, market factors and organisational factors, and organisational performance. The questionnaire was randomly e-mailed to employees of the SA life insurance companies.

5.7 Sampling

The sampling approach is posited by Polit and Beck (2017) as the means of finding situations, contexts, and participants capable of providing rich accounts of a phenomenon of interest to solve a research question. There are varied definitions of sampling, and consistently.

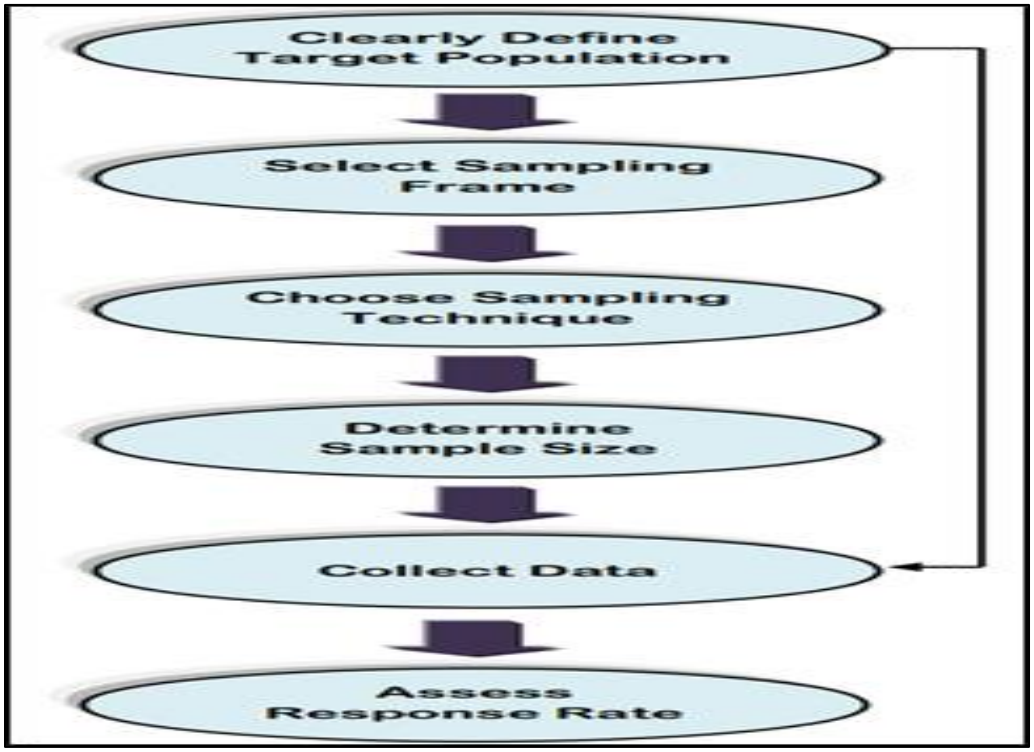
Adwok (2015) advocates various definitions of sampling by authors in social research. Equally important, sampling indicates a representative subset of the population (Showkat & Parveen, 2017). Furthermore, Showkat and Parveen (2017) explain sampling as a process of choosing a sample of the population to study. According to Leedy and Ormrod (2016), sampling identifies the population from which data is collected.

The process of sampling in statistics refers to taking a specified number of observations from a larger sample size (Rahi, 2017). Also, Glicken (2003) states that sampling is the process of choosing a smaller group of respondents to tell researchers what a larger population might produce should they have asked every member of the larger population the same questions.

Researchers must develop a sampling plan stating a sampling method, size, and process to recruit research participants (Moser & Korstjens, 2018). In this quantitative research, the sampling process included a subset of the larger population to make conclusions about the whole population (Babin & Zikmund, 2016).

This research followed Taherdoost's (2016a) recommended steps for developing the sampling procedure for the empirical study, as illustrated in Figure 5.5 below, to answer this study's research problem.

Figure 5.5: Process Steps



Source: (Taherdoost, 2016a, p.19)

5.7.1 Sample Population and Method

Greener (2008, p. 48) defines a population as "the full universe of people or things from which the sample is selected". According to Parahoo (2014,p.152), a population is "the complete number of components, organisations, individuals, or items – that are chosen to be measured as the sample of the study". A population is a group of people from which a research sample is drawn (Taherdoost, 2016a). Etikan, Musa and Alkassim (2016) also stress that a sample is a portion of the population or universe.

Furthermore, Etikan et al. (2016) believe that the population includes a total quantity of cases that are the subset of the research study, suggesting that the population generally has people and objects. This denotes people or items the researcher will investigate to draw inferences from data gathered from their responses (Rahi, 2017).

It is not practical, however, for the researcher to include every person, member, or case in the study (Showkat & Parveen, 2017). Zefeiti and Mohamad (2015) likewise advocated studies with a considerable population require the researcher to choose a precise sampling technique to generalise results.

However, it is not viable for researchers to gather data from all cases due to time constraints and the number of resources required to analyse the entire population. Therefore, they apply sampling methods to reduce case numbers (Taherdoost, 2016a).

This implies the researcher's ability to justify a meaningful sample to represent the population for the study (Saunders, Lewis & Thornhill, 2016). In doing so, a researcher should choose a required sample to study from the entire set of cases to generalise the results to the whole population (Zefeiti & Mohamad, 2015). The sampling method, therefore, determines how findings can be generalised.

According to Leedy and Ormrod (2016), researchers need to determine that the sample represents the population using strategies to select a suitable sample that addresses bias and possible distortion of data in their study. Taherdoost (2016a) supported this view by saying that researchers need to decide on a broad sampling technique before choosing the specific sampling technique for the study.

In effect, researchers should identify the section of the population that is carefully selected for the research; this selection process is based on probability or non-probability sampling (Showkat & Parveen, 2017). Singleton Jr and Straits (2017) also state that a sampling design consists of probability and non-probability sampling. Furthermore, Singleton Jr and Straits (2017) maintain that probability sampling includes a random selection procedure at some point.

Consequently, probability sampling is most closely connected with surveys and experimental research methodologies; as a result, a sampling frame is used to generalise research findings (Saunders et al., 2015). In contrast, a non-probability sampling technique mainly involves judgement and uses non-randomized methods to draw a sample.

Participants in this sampling method are chosen because they are easy to access (Showkat & Parveen, 2017). In this research, probability sampling was employed to select respondents for this study. A probability sampling assured the probability that a sample was a representative population of this study and had an equal chance of inclusion (see, for example, Rahi, 2017; Showkat & Parveen, 2017; Saunders et al., 2016). This study's population units were randomly selected to reduce bias associated with selecting subpopulations (Robson, 2002).

In this method, the probability of selection for each unit was determined, and credible estimates of the sampling error were created concurrently to make inferences about the population (Fellegi, 2003). This study is quantitative, and it generally relies on random or representative sampling to generalise the findings from the sample to the population (Rudestam & Newton, 2014).

For this research, simple random sampling was employed to ensure that each participant had an equal opportunity to participate in the study and to avoid bias and lack of representativity (Rahi, 2017). Also, to eliminate preferences and avoid bias or lack of representativity. In this sampling method, all elements have an equal probability of being selected (Rahi, 2017; Showkat & Parveen, 2017; Saunders et al., 2016; Shah & Al-Bargi,2013; Taherdoost, 2016).

For this study, a simple random sampling was adopted, and the estimated sample was derived from the online Roasoft sample size calculator and tested with a statistical formula. The target population for this study was 130000, divided into four SA life insurance companies (See Table 5.1 hereunder).

Table 5.1: Sample Population and Size

Sample Population	Population Size	Data Gathering Tools
Liberty Holdings	39000	Questionnaire
MMH	32500	Questionnaire
PPS	19500	Questionnaire
Sanlam	39000	Questionnaire
Ideal sample	130000	

Source: Authors' compilation

The life assurance industry was selected as a sample for this study. The researcher identified and approached registered life assurance that holds a valid license with the Financial Sector Conduct Authority (FSCA). The target population was randomly selected employees of the SA life insurance industry.

The selection criteria for these companies were due to their market share, the value of new business across different segments, and their head offices in SA. All the randomly selected employees were South African residents, resulting in a geographically equivalent group with similar exposure to external business issues.

The insurance industry in South Africa represents the country's financial services businesses, which increases the likelihood of generalizing the findings to organisations in this area. These insurance businesses are publicly traded on the Johannesburg Securities Market and have several stock exchange listings. As a result, the public has access to a wealth of information on these businesses.

5.7.2 Sample Size

The sample size is an essential aspect of any empirical study. It should represent a given population to make inferences about the population based on the sample characteristics (Ahmad & Halim, 2017, p.20).

In every research effort, determining an appropriate sample size is critical since it affects the quality of the study's conclusion (Boddy, 2016; Coyne, 1997). Ahmad and Halim (2017) advocate that excessive and inappropriate sample sizes influence a research's quality and precision. Selecting the sample size balances the need for statistical power, economy, and timelines.

Additionally, Ahmad and Halim (2017) maintain that the design of the sample size is more vital than its absolute size, thus suggesting that a large unrepresentative sample is less effective than a smaller sample. Conversely, Taherdoost (2016a) reveals that in terms of random samples, they need to be of adequate size for the researcher to avoid sampling errors and biasness. The researcher then should choose the absolute sample size proportional to the population's complexity and the statistical manipulation used in data analysis rather than the sample's adequacy (Taherdoost, 2016a, p.24).

Determining the proper sample is a complex process attributed to budget constraints and the amount of acceptable sampling error involved. Samples are therefore selected before data collection to ensure that the confidence interval is narrowed enough and useful for decision-making (Ahmad & Halim, 2017). This study uses a structured questionnaire to collect data for the selected population.

Survey sampling improved the speed of data collection, accuracy of results and cost efficiency (Saunders et al., 2015). Quantitative approaches employ smaller groups of individuals to make conclusions about bigger groups that would be prohibitively expensive to investigate, even though greater sample sizes are known to minimise sampling mistakes at a diminishing rate (Ahmad & Halim, 2017, p.21). This quantitative study uses random or representative sampling to generalise the findings from the sample to the population (Rudestam & Newton, 2014). The researcher employed the correct sample

technique to ensure that large samples were generalised and to reduce the probability of sample bias (Zikmund, 2003).

Meanwhile, a random sample was selected to avoid bias or lack of representativity. In tandem, all subjects or elements had an equal probability of being chosen. Simple random sampling was used based on the principle that every subject in this research project had the same probability of being chosen (Berinsky, 2008; Rahi, 2017; Showkat & Parveen, 2017; Saunders et al., 2016; Taherdoost, 2016).

Taherdoost (2016a, p.24), and Zefeiti and Mohamad (2015, p.5) proclaim that several approaches and statistical formulas are used to calculate and determine the sample size. This research used a computer program to generate random numbers from a numeric list of the sample size for this study.

According to Saunders et al. (2015), researchers should estimate the population's characteristics at a 95% confidence level and a margin of error between 3% to 5% of the valid values for most business and management research. As for this study, quantitative measures narrowed the sample distribution (Zikmund, Babin, Carr & Griffin, 2013).

The estimated sample size for this study was derived from the online Raosoft's sample size calculator and two statistical formulas to assure correctness. Since the most common confidence intervals are 90%, 95%, and 99%, this study's sample size was calculated using a response rate of 50%, a confidence interval of 95%, and a margin of error of 5% (See Table 5.2 hereunder).

Furthermore, The Freund and Williams formula, cited by Uzoamaka et al. (2017, p115 a), was used to calculate the sample size for this study. Formula A and B computed the sample size for this study.

Table 5.2: Raosoft Sample Size Calculator

Description	Parameters
Confidence interval	5%
Confidence level	95%
Population	130000
Ideal sample size	384

Source: http://www.raosoft.com/ samplesize.htm

Formula A depicts the sample size formula derived from the pilot study data, with p = 0.50 and q = 0.50, where η = sample size, p= percentage of positive responses, q = percentage of negative responses, e = margin error, and Z = confidence level. This study employed a z-score of 1,960, representing a two-tailed 95% confidence interval and a margin error of 5%. Furthermore, Formula B represents the sample size calculation using the 0.50 standard deviation, 95% confidence level, and a 5% confidence interval.

Formula A: $\eta = Z^2 \times p \times q / e^2$

$= [(1.960)^2 \times (0.50 \times 0.50)] / (0.05)^2$

$= (3.8416 \times 0.25) / 0.0025$

$= 0.9604 / 0.0025$

$= 384$

Formula B: $n = (z\text{-score})^2 \times \sigma \times (1- \sigma)/ e^2$

$= [(1.960)^2 \times 0.50 (1-0.50)]/ (0.05)^2$

$= (3.8416 \times 0.25)/ 0.0025$

$= 0.9604/ 0.0025$

$= 384$

As can be seen, Formula A and B determined that 384 samples were needed for this study. The sample size was increased by up to 50% in the first distribution of the survey to ensure minimum samples are met (Bartlett, Kotrlik & Higgins, 2001).

5.8 Data Collection Strategy and Instrument

According to Creswell and Guetterman (2019), data is the process of obtaining information from various sources to answer research questions. Data collection aims to generate accurate information that translates to rich data to provide credible answers to the research question.

This signifies that data collection techniques influence the research layout (Zikmund et al., 2013). In effect, survey research data is collected from multiple channels such as telephone, post, interview, e-mail, internet-based surveys, and by hand delivery (Ary, Jacobs & Razavieh, 2010; Dillman, Smyth & Christian, 2009; Hair, Black, Babin & Anderson, 2017; Singleton Jr & Straits, 2017). This cross-sectional study examined variables and collected data at a specific point in time (Zikmund et al., 2013).

In this quantitative research, empirical methods were employed, and research data was collected and analysed systematically to attain research outcomes (Dan, 2017). Data for this research was then analysed, organised, structured, and represented numerically to build accurate and reliable measurements for statistical analysis (Goertzen, 2017).

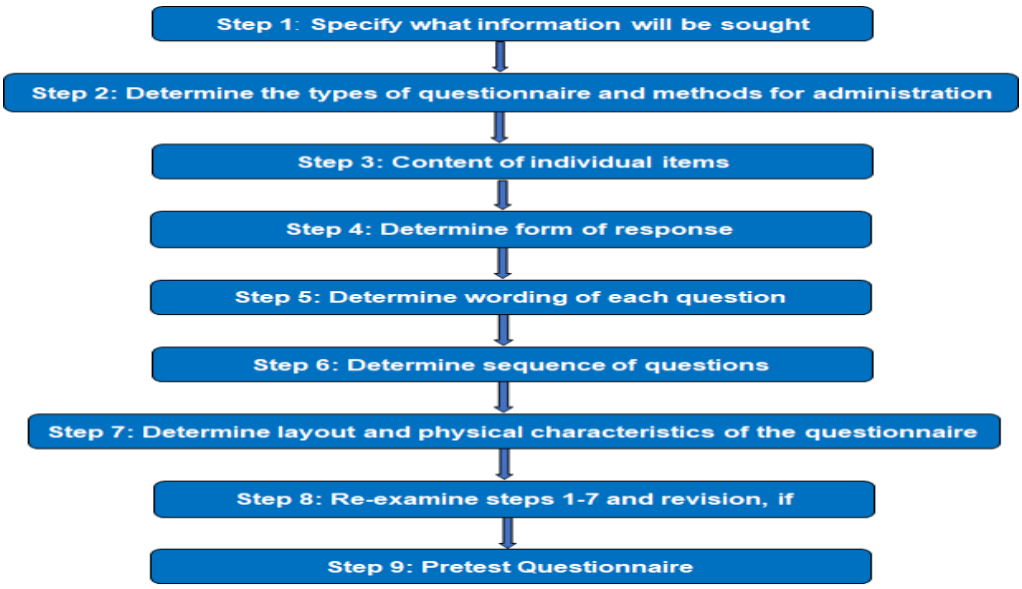
5.8.1 Questionnaire Design and Development

Harlacher (2016, p.2) defines a questionnaire as “a set of questions administered to individuals to gather useful information”. As a result, questionnaire design is a methodical process that necessitates researchers to follow a set of stages (Burns & Bush, 2010).

The researcher must articulate goals from the beginning to avoid the risks of gathering incomplete or misleading data (Fink, 2015). In this study, a questionnaire was created to collect the information needed to answer the research questions and meet the study's key goals (Saunders et al., 2015).

This research employed Churchill and Iacobucci's (2002, p.315) nine steps process to develop the questionnaire for this project to ensure accuracy and usefulness of information (See Figure 5.6 below). The questionnaire design was aligned with the structure of this study’s conceptual framework.

Figure 5.6: The Questionnaire Procedural Steps



Source: (Churchill and Iacobucci, 2002, p.315)

A large sample size is necessary if the researcher intends to generalise the study (Hair et al., 2019a). Quantitative research involves larger samples, and less time was needed to collect data (Rahman, 2017). In addition, quantitative research pays more attention to data that can be measured so that the research outcomes can be compared, generalised, and summarised (Goertzen, 2017).

Quantitative data was gathered through questionnaires and surveys developed and structured to provide numerical data for the researcher to perform statistical analysis and describe, summarise, and present data graphically and in tables (Rae, Salhin, Taheri, Porter, Köning & Valantasis-Kanellos, 2016).

As for data collection, the researcher followed three distinct steps: designing the instrument, sample size, and implementation of an electronic survey. The data collection process involved using multiple sources and data collection methods to minimise bias and guarantee the quality of the research data (Sekaran & Bougie, 2016). Data for this study were collected from both primary and secondary data, so empirical methods were used in this quantitative research (Dan, 2017). This study is quantitative, and the researcher pursued the positivist paradigm.

Primary data for this research was collected through self-administered questionnaires to ensure the authenticity and objectivity of the responses. The literature review was gathered from peer-reviewed academic journals and books to assist with the questionnaire's design and develop a preliminary model for the research. Secondary data from a variety of sources were examined for relevance to the research.

To gather and process data for this study, a questionnaire was created using Google Drive's Form tool. The questionnaire was developed to cover seven items based on the biographical profile scale in Section “A” for this research. In tandem, Section “B” of the questionnaire consisted of eighty-four Likert-scale-type questions (see Appendix B).

The questionnaire items comprised 17 and 84 closed-ended questions in Sections A and B. For this research, closed-ended questions were employed, and data generated from these questions were analysed more efficiently than data generated from open-ended

questions (Fink, 2015; Kline, 2005b). This research also used closed-ended questions because of limited time and resources (Kline, 2005b).

5.8.2 Reliability and Validity of Data Gathering Instrument

In any research project, critiquing the study results increases transparency and reduces research bias. Reliability and validity are the two most important and fundamental criteria in evaluating any measurement instrument or tool for successful research (Mohajan, 2017, p.1).

In quantitative research, reliability and validity enhance the accuracy and evaluation of the results (Heale & Twycross, 2015). Reliability and validity play a significant role in ascertaining the sincerity of the data collection tools for good research (Mohajan, 2017).

According to Creswell and Poth (2016), verification is the first step in achieving the validity of a research project. Furthermore, Creswell and Poth (2016) affirm that validity is based on credibility and external reviews to perform a research outcome. Internal validity investigates how the study was designed, conducted, and analysed to answer the research question (Andrade, 2018).

In contrast, reliability measures the accuracy of the research instrument to generate reliable findings and if the research outcomes yield the same results consistently when used and repeated on the same occasions to measure the same event (Heale & Twycross, 2015). The researcher will then ensure the elimination of random errors in the data obtained from the questionnaires (Mohajan, 2017).

In this project, the researcher considered the validity and reliability of the instruments collecting data for this study. For this reason, a structured-administered questionnaire was used to collect relevant information most reliably and validly. Content validity adequately covers the investigative questions and variables guiding this research. This study contains a representative sample of the overall subject matter of interest. Conclusions were drawn from the sample population of which content validity was satisfied (Cooper & Schindler, 2014). In this research, rigorous statistical tests were used to ensure the objectivity of this study.

Validity was preferred as it generated adequate coverage of the investigative questions guiding this study. According to Abbas, Gravell and Wills (2010), the sample size informs the reliability of factor analysis. MacCallum, Widaman, Zhang and Hong (1999) found a lack of validity in common rules of thumb and established guidelines for sample size in factor analysis. For instance, Guilford (1954) argued that the required sample size for factor analysis should be 200. Cattell (1978) proclaimed the minimum desired sample to be 250.

Meanwhile, a rating scale for the adequate sample size for factors is graded as very poor for 50, 100 as poor, 200 as fair, 300 as good, 500 as very good, and 1000 as excellent (Comrey & Lee,1992; Comrey, Backer & Glaser, 1973; Castello & Osborne, 2005; De Vellis, 2017).

Additionally, Hoe (2008), and Singh, Junnarkar and Kaur (2016) suggest that any sample size greater than 200 offers adequate statistical power for data analysis, and factor analysis was employed in this study's sample size of 276 to inform its reliability. In this quantitative research, findings were generalised and uncovered behaviours and trends from the sample (Goertzen, 2017).

Moreover, trends were identified in this study's data sets and respondents (Goertzen, 2017). Factor analysis was also used to reduce data sets to understand the variables of this study (Abbas et al., 2010). In a correlation matrix, data was reduced to a collection of components using the least number of explanatory ideas to explain the highest amount of shared variation (Field, 2005).

Meanwhile, indicator loadings discovered patterns amid variables of this study (Abbas et al., 2010), which means that factor analysis assessed the validity of the questionnaires to discover simple patterns among the variables.

Similarly, the researcher used the internal consistency approach to evaluate the reliability of the questionnaire responses. Every item was associated with every other item throughout the total sample, and the average inter-term correlation was used as the reliability index (Heale & Twycross, 2015).

Cronbach's alpha coefficient was then used to assess the internal reliability of the questionnaire items used in this study. Furthermore, Cronbach's alpha was also used to compare two or more measures concerning their internal consistency (Diedenhofen & Musch,2016). See Chapter 6 for the discussion of the results of the reliability validity of the internal correlated items.

5.8.3 Pre-test Questionnaire

According to Hilton (2017, p. 1), pre-testing ensures that questions function as intended and are understood by people who are most likely to reply. Without pre-testing the questionnaire, problems detected will be carried forward into the main statistical analysis.

Because it delivers accurate, trustworthy, and impartial data, pre-testing is a key aspect of the questionnaire design and development. It also identified any possible issues with the questionnaire, such as complexity, duration, phrasing, and how it operates, as well as whether any revisions are required before the survey begins (Creswell, 2009; Sekaran & Bougie, 2016).

The sample size for pretesting a questionnaire, according to Wilson (2012, p.178), is usually small, ranging from 10 to 40 respondents, depending on the variety of the target group. In contrast, Burns and Bush (2010, p.354) claim that a sampling of 5 to 10 responders is sufficient for pretesting.

For this study, pre-testing of the questionnaire was done using a default sample size of 30 respondents to find even minor errors (Perneger, Courvoisier, Hudelson & Gayet-Ageron, 2015). Twenty surveys were returned, indicating a response rate of 67%. This step was crucial for capturing any possible phrasing issues and the questionnaire's complexity, length, and duration.

This stage's outcomes were deemed successful. One female participant, for example, stated that she had difficulty answering her age in years and recommended that it would be preferable to offer age in interval groups. Another commenter had some concerns about the phrasing of one of the questions. The researcher then attempted to simplify and clarify the query.

According to the results, the questionnaire items were properly phrased and easy to comprehend. Consequently, preliminary findings for the questionnaire's reliability and validity were acquired before moving on to the data gathering stage.

5.8.4 Pilot Study Results

Since this study was conducted in South Africa, it was necessary to pilot test the questionnaire before using it to assess its validity and reliability and to enhance the questions, structure, and scales (Creswell, 2009).

The major goal of the pilot project is to ensure that the questionnaire items are easy to read, understand, and complete, as well as to see if the data obtained answers the research objectives and has content validity (Taherdoost, 2016b). The questionnaire was given to a randomised sample of 30, with 20 valid questionnaires returned, representing a response rate of 67%. Cronbach's alpha coefficient test was used.

According to Field (2013, p.710), Cronbach's alpha needs to be equal to or greater than 0.700, though sometimes a value of 0.600 is acceptable. Similarly, some studies have indicated Cronbach's alpha thresholds as acceptable, sufficient or satisfactory to be equal to or greater than 0.700 in five instances and greater than 0.700 on three occasions (Taber, 2018, p.1278).

Some studies have also reported 0.700 or 0.600 as acceptable values (See for example, Griethuijsen, van Eijck, Haste, den Brok, Skinner, Mansour, Savran Gencer & BouJaoude, 2015). For this pilot study, all alpha values exceeded the reliability recommended benchmark of 0.700 (See Table 5.3 below).

The Cronbach's alpha results of the pilot study showed that all constructs under investigation produced satisfactory results ranging from scales of 0.858 to 0.967, respectively, thus demonstrating consistency and reliability as all the study's constructs had a Cronbach's alpha that is greater than 0.700 (See Table 5.3 below). Following Field's (2013, p.692) advice, factor loadings less than 0.300 were eliminated during the pilot study. Furthermore, Field (2013, p.647) advocates that a factor with four or more loadings

greater than 0.600 “is reliable regardless of sample size.” The factor loading results of the pilot study produced reliable results ranging from 0.700 to 0.826 (See Table 5.3 below).

Table 5.3: Reliability of Scales During the Pilot Study

Constructs	No of Items	Chronbach's α	Factor Loadings
Organisational Factors			
Leadership	6	0,910	0,774
Strategy	6	0,912	0,791
Structure and Process	6	0,934	0,781
Employee	6	0,871	0,781
Reliability and Validity Test	24	0,907	0,782
Market Factors			
Competition	5	0,873	0,825
Customers	5	0,916	0,815
Information Providers	5	0,882	0,803
Technology	5	0,869	0,802
Reliability and Validity Test	20	0,885	0,811
Information Attributes			
Information Accuracy	5	0,925	0,843
Information Credibility	5	0,930	0,836
Information Quality	5	0,940	0,841
Information Usefulness	5	0,917	0,808
Chronbach's α Test	20	0,928	0,832
Employee Role Clarity			
Employee Role Clarity	5	0,858	0,702
Customer Satisfaction			
Customer Satisfaction	5	0,912	0,786
Organisational Performance			
Organisational Performance	5	0,900	0,774
Competitive Intelligence			
Competitive Intelligence	5	0,967	0,828
Overall Reliability Scales	84	0,908	0,788

5.8.5 Instrument Scale Measurement

A questionnaire approach including nominal and ordinal scales was devised in this study. Participants' characteristics such as age, gender, work position, ethnicity, marital status, and the greatest level of education and experience mainly were determined using nominal scales. Participants who indicated that they were not employed were prevented from continuing with the questionnaire.

A Likert scale is a specific rating scale used to measure attitudes and uses symmetrical responses (Dillman et al., 2014; Fink, 2015). Fink (2015), and Kaplan and Saccuzzo (2017) point out that rating scales with four to seven options are commonly used in any research study. As such, response options above seven create a cognitive burden for respondents and lead to unreliable results.

A five-point Likert scale rating was employed to avoid respondents' fatigue and to encourage higher response rates. The five-point Likert scale rating was appropriate for this study since it provides an interval or ratio-based scale, and it is the most potent scale for statistical analysis (Hair, Black, Babin, Anderson & Tatham, 2006). The respondents were asked to rate indicators on a five-point Likert-type rating scale, indicating the extent to which they agree or disagree with various statements (Saunders et al., 2015).

The Likert-scale rating ensured that various statements were generated. An item analysis was performed to evaluate statements on a scale of agreements. The item analysis guaranteed more comprehensive responses and grouped and separated responses based on similarities (Zikmund et al., 2013). Bryman and Bell (2015), and Kothari (2004) assert the following advantages of using self-administered questionnaires in a research study:

- Offer lower costs even with a larger population that is widely spread geographically.
- Self-administered questionnaires are objective, and their answers are in the respondents' own words.
- Respondents have enough time to reflect on the questions to give good answers.
- Respondents who are otherwise not easy to approach can also be reached without trouble.
- Larger samples generate reliable results and offer greater anonymity to the participants

This research chose a structured-administered questionnaire because it was cheap to administer and offered participants greater flexibility to complete anywhere at their own convenience.

The questionnaire was written in precise and simple language and scaled to yield specific answers reflecting the respondents' actual point of view. The structured questionnaire was uploaded to Google Drive's Form website: https://forms.gle/qQ6WQNF7udm1DBfVA.

Ravichandran and Arendt (2008) have suggested that establishing contact with critical corporate representatives increases the likelihood of attaining higher response rates. For this study, letters of permission to conduct research were obtained from Liberty, MMH, PPS and Sanlam, thus granting the researcher permission to conduct his research (See Appendix D).

The researcher sent an e-mail to key business executives outlining the study's overall goal and survey instructions; respondents were informed that their participation was optional and that they may withdraw at any time without repercussions. Furthermore, the participants were told that all the information gathered for this study would remain strictly confidential. On this e-mail, a Google Drive's Form link has a participant's consent letter covering confidentiality and anonymity issues.

Each organisation's key person helped identify and mail qualified research participants in their respective organisations. The structured questionnaire was randomly e-mailed to this study's research participants. All the participants were asked to complete the questions on Google Drive's Form website, thus forming a base for data analysis.

As a result of the outbreak of the COVID-19 pandemic, the participants were granted a period of two months to answer the questionnaire as most of these participants worked remotely and away from their main offices citing challenges to access the internet and quality of connectivity.

Moreover, the researcher followed up with respondents and the key persons by emailing successive reminders to encourage each participant to complete the questionnaires on time. Importantly, Taherdoost (2016a) states that it is very rare for researchers to attain 100 per cent response rates in their study due to participants' inability to respond, refusal to respond, and the researcher not being able to make contact with located participants.

Neuman (2014) contends that one of the most significant disadvantages of a self-administered mail questionnaire is lower response rates resulting from respondents' perception of the content being of sensitive nature. In this research, 384 questionnaires were distributed, and 278 questionnaires were received, from which 276 were completed and usable, thus attaining a response rate adequacy of 72 percent, which is acceptable for this study.

5.8.6 Data Preparation Process

In empirical research data, the collection stage depends on a particular research design, sampling procedures, control variables, and management of missing data (Aguinis, Hill & Bailey, 2019). Data preparation is the first stage in analysing research data to ensure that raw data is converted into meaningful and reliable information.

According to Borg, Nguyen and Tierney (2021, p.1), missing data are unobserved values, meaning that the population of interest might not be sampled appropriately, inducing bias in a study's results. Large data sets include errors of diverse forms. For instance, respondents may fill fields incorrectly or skip survey questions accidentally, while some mistakes are attributed to equipment failure or intentionally not recording values (Borg et al., 2021).

Consequently, the probability of missing research data sets is often unavoidable (Newman, 2014). This shows that decisions to handle missing data can profoundly affect the validity and accuracy of the study's results(Borg et al., 2021). Notably, missing untraceable or poorly handled data can undermine the validity and accuracy of the research study (Nakagawa & Freckleton, 2008; Sainani, 2015). As such, missing data should always be imputed, and researchers should explore imputation methods to ensure that they represent the sample appropriately (Borg et al., 2021, p.1).

In this research, missing data occurred randomly, and the probability of an entry being missing depended on the other variables but not on the unobserved value. In SPSS version 24.0, the median of nearby points was used to replace missing data. Editing and coding the data is usually the first step in data processing (Zikmund et al., 2013, p.70).

Data preparation for this study, therefore, involved coding and editing. According to Churchill and Iacobucci (2006), editing ensures that data is comprehensive, consistent, and legible before it is coded. It is transferrable and stored in a computer program. Editing includes looking for omissions, readability, and categorisation consistency in the data gathering forms (Zikmund et al., 2013, p.70).

With the data preparation stage commencing after the data collection, the researcher checked data for accuracy before it was captured into the computer and transformed into usable data to conduct a series of statistical tests before commencing with data analysis (Babin & Zikmund, 2016).

Notably, the researcher conducted basic data checks, checked for outliers, and edited raw research data to identify and clear incomplete data that could impact the accuracy of the results (Aguinis et al., 2019). Before the data was transferred to the computer, the editing process assisted the researcher in correcting responses recorded incorrectly in a section of the questionnaire (Zikmund et al.,2013). The questionnaire was reviewed after the completion of the survey.

The researcher checked for completeness and accuracy of the received questionnaires and prepared them for data analysis. In the editing process, the researcher removed and filled all the empty data fields. The completed questionnaires were rechecked before transferring them to a computer to identify any potential errors or omissions resulting from the edited questionnaire.

As for problems discovered due to non-response, data was adjusted to make it completely consistent or readable (Zikmund, 2003). In addition, the coding process assisted with identifying and classifying answers with numerical scores and character symbols (Babin & Zikmund, 2016). Basically, the researcher established meaningful categories and character symbols for groups of responses by assigning codes before data was tabulated.

The coding process also facilitated computer tabulation so that data entered into the computer is verifiable (Zikmund et al., 2013). This study assigned names to be coded and

captured on the computer. In addition, responses to questionnaires were coded to facilitate inputting data into the computer.

On completion of the data entry process, scale items that were worded negatively were recorded and assigned new values. This study's target variables were evaluated to obtain a composite for items on a scale. Data files were carefully screened to minimise entry errors, and frequencies for each variable were checked to detect out-of-range values.

5.9 Data Analysis

Data analysis is the process of organising research data to gather accurate information for the study (Rae et al., 2016). According to Rajaraman (2016), data analysis is a practice by which large quantities of data are ordered and organised so that valuable information is used to discover new patterns and relationships amongst the variables. In quantitative methods, large data sets are collected and inspected from various information sources (Goertzen, 2017).

In this research, responses from the questionnaires were coded and analysed according to the most prominent themes, patterns, and relationships. Statistical techniques were also employed to ensure accurate analysis. These days, advanced technology is used to analyse, collect and store data at a lower cost (Zikmund et al., 2013). The following section discusses and justifies descriptive, inferential statistics, reliability, validity, model fitness, and predictive relevancy.

5.9.1 Descriptive and Inferential Statistics

Statistical methods were employed in this research to draw inferences from the study's participants. Quantitative data analysis was divided into preliminary data analysis and hypothesis testing. Primary data was then processed and stored in a computer program to generate descriptive statistics and graphs.

The process involved organising large data sets in the sample and reducing them to meaningful summary values and graphs. According to Mishra, Pandey, Singh, Gupta,

Sahu and Keshri (2019, p.67), descriptive and inferential statistics play a significant role in scientific data analysis; hence, they are usually used in most research studies.

For this reason, descriptive and inferential statistics were used in this study. Descriptive statistics are statistical methods that summarise data in a proper and meaningful manner; while inferential statistics provide future predictions about a population by studying a smaller sample (Mishra et al., 2019). Furthermore, Mishra et al. (2019, p.67) assert that descriptive statistics simply summarise a set of observations to communicate the largest amount of information.

Moreover, descriptive statistics delivers information concerning an immediate collection of data (Salkind, 2014). This research used descriptive statistics to identify common themes in the participants' responses to questionnaires. Such descriptive statistics were quantifiable and provided more insights into the responses to the questionnaires.

As for inferential statistics, they have a semi-different role to play in research than descriptive statistics. According to Salkind (2014, p.9), inferential statistics are utilised to extrapolate from smaller data sets to a possibly larger one. Inferential statistics conclude from data subject to observational errors and sampling variations (Mishra et al., 2019, p.67).

Inferential statistics produce estimations or predictions for the sample, and they also generate cause and effect while making predictions and providing insights between variables (Anderson, 2003). For this reason, inferential statistics were employed to collate data from the sample of this study to make inferences about the larger population from which the sample was drawn to draw conclusions from the sample and ensure that data was generalised to the entire population.

This research employed a simple random sample, and inferences about the population were drawn based on the findings from a random sample representing the population (Raines, 2013, p.289). Equally important, Gupta (2012, p.143) proclaims that inferential statistics use hypothesis testing and point estimation. These two concepts assisted the

researcher in making inferences about the population from the sample and testing this study's seventeen hypotheses.

5.9.2 Structural Equation Modelling

Multivariate analysis methods are commonly employed in research because they are probable to evaluate variables' associations (Hair, Anderson & Tatham, 1990). Three multivariate analysis methods are widely used in research studies: multiple regression, path analysis, and structural equation modelling (Kock, 2010).

SEM is a class of multivariate techniques that enables the researcher to examine relationships between the endogenous and exogenous to assess both the measurement and the structural theory through combining factor and regression analysis (Hair Jr et al., 2017a). According to Cepeda-Carrion, Cegarra-Navarro and Cillo (2019, p.67), SEM is defined as " the combination of latent variables and structural relationships".

Furthermore, Cepeda-Carrion et al. (2019, p.69) assert that SEM is based on latent variables that are measured by indicator variables. Since then, SEM has become a quasi-standard for analysing latent constructs of interest (Hair, Hult, Ringle, Sarstedt & Thiele, 2017, p.616).

Importantly, SEM can estimate multiple constructs' direct, mediating, and moderating effects at once to assess connections that are difficult to untangle and study (Ringle, Sarstedt, Mitchell & Gudergan, 2020).

Meanwhile, SEM relies upon the research objective, inner model specification, the outer model, and the data used for evaluation (Hair et al., 2014a). This research model is complex, and multivariate analysis methods were employed to estimate the multiple variables of the model (Hair et al., 2011).

Complex modelling cannot be tested using first-generation statistical tools, whereas complex mathematical models can be tested using SEM (Gefen et al., 2000). This study used SEM with Partial Least Squares to estimate the conceptual model's direct, mediating, and moderating effects of multiple constructs.

5.9.3 Partial Least Squares-Structural Equation Modelling

Partial Least Squares (PLS) and SEM are extensively used in many other fields where multivariate statistical analyses are employed (Kock, 2017). Furthermore, PLS-SEM is widely used in business research (Hair, Ringle & Sarstedt, 2011; Kock, 2010; Kock, 2014). This notion validates Hair, Sarstedt, Pieper, and Ringle's (2012c) report that PLS-SEM multivariate analysis techniques are applied progressively in management research.

Richter, Sinkovics, Ringle, and Schlägel (2016b) also observed an upsurge in the number of PLS-SEM applications in international business in the past few years. Researchers can either utilise the Covariance-Based SEM (CB-SEM) or Partial Least Squares SEM (PLS-SEM) to estimate structural equation models (Cepeda-Carrion et al.,2019; Marcoulides, Chin & Saunders, 2009).

The research objectives of the investigation determine whether CB-SEM or PLS-SEM should be used. CB-SEM will be an excellent approach to utilise if the study's research purpose is theory testing and confirmation. PLS-SEM would be appropriate for a study if the goal is prediction and theory development (Hair et al., 2011, p.140). The type of latent variables used in a study is the main difference between CB-SEM and PLS-SEM (Rigdon, 2016).

Because of the types of latent variables it uses, PLS-SEM is a type of structural equation modelling based on variance and components (Rigdon, 2014). Meanwhile, composite-based SEM, particularly Partial Least Squares (PLS) path modelling, has grown in popularity in marketing (Hair et al., 2017, p.616).

As a result, PLS employs two sets of linear equations: measurement and structural models (Garson, 2016). The measurement model in PLS specifies the relationship between unobserved or latent variables. In contrast, the outer model specifies the relationship between a latent variable and its manifest variables (Hair et al., 2014b).

Essentially, the inner and other models are also known as the structural ad measurement model (Hair et al., 2014a). Wold's (1974, 1982), and Lohmöller's (1989) PLS-SEM continues to enjoy popularity in various research disciplines (See for example, Hair,

Sarstedt, Ringle & Mena, 2012a; Henseler, Ringle & Sinkovics, 2009; Lee, Petter, Fayard & Robinson, 2011; Ringle, Sarstedt & Straub, 2012).

PLS-SEM is frequently utilised across different management disciplines, comprising organisational research, strategic management, and knowledge management (Cepeda-Carrion et al., 2019; Hair, Sarstedt, Pieper, & Ringle, 2012b; Sosik, Kahai, & Piovoso, 2009).

As for strategic management, PLS-SEM has been recognised for its flexibility in handling various modelling problems (Hulland, 1999). Hair et al. (2012b), in their reviews of the use of PLS-SEM in the strategic management field, found that the methods distribution was not as widespread as in other disciplines. Furthermore, Hair et al. (2012c) also found problems associated with PLS-SEM use in strategic management. In contrast, Hair et al. (2013) stress that even with the lower dissemination of PLS-SEM found in the past, its application in strategic management presents various opportunities.

Previously, Ali, Rasoolimanesh, Ringle and Ryu (2018), and Rigdon (2016); Rigdon, Sarstedt and Ringle (2017) have indicated that it was vital for researchers to use techniques that are congruent with the type of model estimated. In this research, PLS-SEM was employed because of its suitable data analysis technique for this study's complex conceptual model. In addition, PLS-SEM was chosen for this study based on the research objective, specification, and model examination (Hair et al., 2014a).

Because of its most prominent research methods across various disciplines, PLS-SEM was used to estimate complex cause-effect relationship models with latent variables (Cepeda-Carrion et al., 2019). Specifically, SEM and SmartPLS software 3.3.3 evaluated the causal relationships between variables of this study (Salehi & Ghaemzadeh, 2018).

Hair, Babin, Money and Samouel (2003) suggested a minimum sample size of 200 appropriate for Structural Equation Modelling (SEM). Also, Hair et al. (2014a) contended that a minimum sample size of 500 and above is required for a complex model with more than seven constructs to perform regression-based SEM.

However, Rigdon (2016) posited that PLS-SEM works effectively with smaller sample sizes when other techniques fail. This is attributed to the ability of PLS path modelling to produce parameter estimates on very small sample sizes. Still, researchers should question the value of those estimates beyond simple data descriptions (Rigdon, 2016).

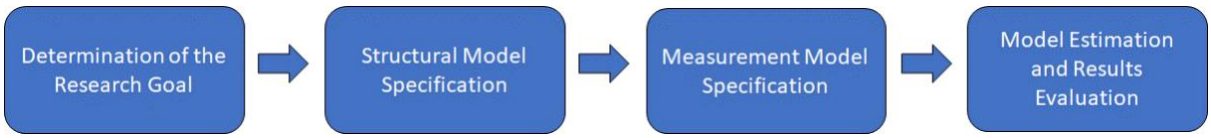
On the other hand, Hair, Henseler, Dijkstra & Sarstedt (2014b) assert that PLS can estimate complex models with smaller sample sizes compared to factor-based SEM even if it is unable to perform simultaneous estimation of all constructs in the model.

Hair et al. (2017) found that PLS performs better in statistical power than other methods. Therefore, PLS-SEM is valuable when employed with small sample sizes in robustness, estimations, and statistical power (Reinartz, Haenlein & Henseler, 2009). In contrast, Hair et al. (2017) state that PLS-SEM works effectively with a wide range of sample sizes.

PLS-SEM, therefore, works efficiently with a wide range of sample sizes in models that have increased complexity. PLS-SEM solves wide-ranging problems CB-SEM methods due to its ability to handle data with fewer restrictions (Hair et al., 2011).

In this project, multivariate statistical analysis with dependence techniques was employed because the variables in this study involved a distinction between dependent and independent variables, thus forming the basis for PLS-SEM. PLS-SEM was suitable since it had no practical limitations to integrating more items into the path model of this study's conceptual framework (Ringle et al., 2020).

Figure 5.7: PLS-SEM analysis process



Source:(Ringle et al., 2020, p.5)

PLS-SEM determines the parameters of a set of equations in an SEM by combining principle components analysis with regression-based path analysis (Mateos-Aparicio, 2011, p.19). This research has mediating and moderating variables; PLS-SEM was used to estimate reflectively specified constructs of the research model (Nitzl, Roldan & Cepeda, 2016).

The researcher, therefore, adopted the process suggested by Ringle et al. (2020) in Figure 5.7 above to facilitate the PLS-SEM analysis process. This research has established connections between constructs through paths representing 17 hypotheses to capture the study's complex conceptual model's direct, mediated, and moderated effects. SEM-PLS was employed to handle many indicators and constructs of the research model, estimate reflectively specified constructs, and manage small sample sizes with care (Ringle et al., 2020).

PLS-SEM performs effectively with complex models and sample sizes, as this is the case in this research (Willaby, Costa, Burns, MacCann & Roberts, 2015). Equally, PLS-SEM could model latent constructs under conditions of non-normality with small to medium samples (Kock, 2016). Richter, Cepeda, Roldán, and Ringle (2016) used PLS-SEM to generate latent variable scores, which were then used in subsequent analyses.

By allowing for estimations in reflectively stated measurement models, PLS-SEM enabled the researcher to answer the study's research topic (Sarstedt, Hair, Ringle, Thiele & Gudergan, 2016). SmartPLS software was used to evaluate the measurement and structural model and estimate the path model for this study. PLS-SEM employed SmartPLS software to evaluate hypothetical relationships between variables (Salehi & Ghaemzadeh, 2018).

5.9.4 Evaluating Measurement and Structural Models

A path is developed using factor and multiple regression analysis to examine the structural relationships between measured and latent constructs (Bollen, 2002). The measurement and structural models are the foundations of SEM. The structural model represents the theory that explains how constructions are related to other constructs,

whereas the measurement model represents the theory that describes how measured variables represent the theory (Schumacker, 2017).

The structural model depicts the structural connections between the constructs, whereas the measurement models describe the relationship between each construct and its associated indicators (Sarstedt, Ringle & Hair, 2017, p.3). The structural and measurement models in PLS-SEM are referred to as inner and outer models (Sarstedt et al., 2017, p.3).

Researchers must use structural and measurement theories to define the relationships between the path model's elements (Sarstedt et al., 2017). In particular, structural theory specifies which latent variables should be considered when analysing a phenomenon and its relationships, whereas measurement theory specifies how latent variables should be measured (Sarstedt et al., 2017).

As for measurement models, researchers can choose between reflective and formative measurement models (Coltman, Devinney, Midgley & Venaik, 2008). This study's complex structural model has many constructs and indicators; therefore, PLS-SEM was more appropriate for this research. The following subsections discuss the process that was followed to evaluate this study's measurement and structural models.

5.9.4.1 Formative and Reflective Constructs

According to Yahaya, Murtala and Onukwube (2019, p. 6), structural equation modelling measurement models can be formative or reflective. This denotes that latent variables can be displayed using formative or reflective indicators. PLS-SEM can handle formative and reflective measurement models (Hair et al., 2011, p. 141). This view is supported by Garson (2016,p.18), who maintains that reflective and formative models are supported by both traditional SEM and PLS-SEM methods.

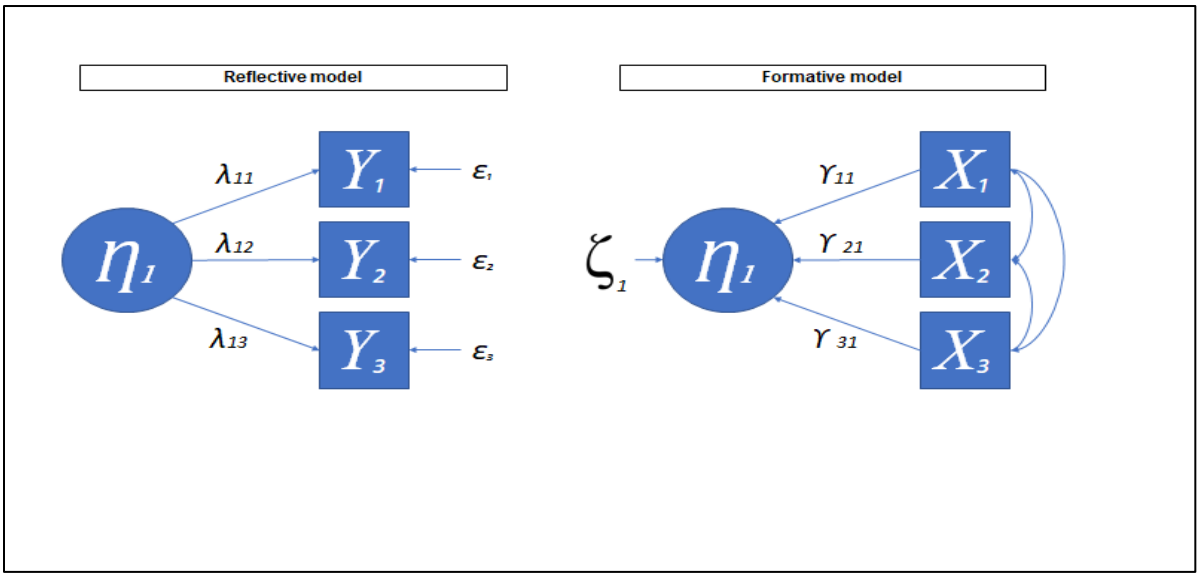
SmartPLS essentially supports both reflective and formative learning methods. To successfully assess measurement models, researchers must distinguish between reflectively and formatively stated constructs (Ringle et al., 2020). According to Garson (2016, p.17), a route model is reflective if causal arrows connect the latent variable (factor)

to the measured indicator variables in the path diagram. The reflective and formative indications are illustrated in Figure 5.8 below.

If the arrows in a route model point from the observable measurements to the latent variables, it is considered formative (Garson, 2016). Furthermore, according to Garson (2016, p.18), reflective models presume that a factor represents "reality" and that measured variables constitute a sample of all potential indications of that reality.

Reflective indicators are functions of the latent construct, and changes in the indicator variables reflect changes in the hidden construct (Hair et al., 2011, p.141). This means that the effect of latent variables will still have the same meaning even if one indicator is being let go from other items.

Figure 5.8.: Reflective and Formative Models



Source: (Edwards and Bagozzi, 2000, pp.161-162)

Figure 5.8 above demonstrates that indicators reflective models represent items reflecting all the latent variables they are measuring (Garson, 2016, p.18).

Ringle et al. (2020) affirmed that examining the indicator loadings in reflectively measured constructs is vital. In effect, internal consistency is essential for reflective constructs. The measurements should be checked for reliability using Cronbach's alpha or other reliability methods (Petter, Straub & Rai, 2007, p.646).

Cronbach's alpha is a conservative reliability metric since it underestimates construct measure dependability. Composite dependability, on the other hand, is often an accurate assessment since it incorporates the exterior loadings (Hair Jr, Hult, Ringle & Sarstedt, 2017, p.301). Essentially, researchers must investigate internal reliability to ensure that Cronbach's alpha and composite reliability are higher than 0.700 and below 0.950 to be regarded as satisfactory (Hair Jr et al., 2017b).

Additionally, Petter et al. (2007, p.646) advocated that reflective measures should be unidimensional. However, if the reflective items are assessing the same aspect of the construct and the content validity of the construct is unaffected, all but one of the reflective items might be eliminated from the measure, yielding a construct with the same content validity (Petter et al., 2007, p.646).

Thus, items with poor item-to-total correlations should be eliminated from a scale during construction to increase internal consistency dependability (Spector, 1992). Because the items are all sampled from the same subject domain, this proposal is appropriate for reflecting indicators (Mackenzie, Podsakoff & Jarvis, 2005, p.710).

As for formative models, the set of indicators collectively represents all dimensions of the latent variable. In so doing, formative models assume that indicators are "reality" and are all the dimensions of the factor (Garson, 2016, p.19). Because changes in the indicators are assumed to produce changes in the latent construct value, changes in the indicators influence changes in the latent construct value (See for example, Diamantopoulos & Winklhofer, 2001; Diamantopoulos, Riefler & Roth, 2008).

When a dimension in a formative model is dropped, it causes the meaning of the latent variable changes (Garson, 2016). MacKenzie et al. (2005, p.712) supported this view by proclaiming that "dropping a measure from a formative-indicator model may omit a unique

part of the conceptual domain and change the meaning of the variable because the construct is a composite of all the indicators".

This signifies that dropping low item-to-total correlations from the scale to enhance internal consistency reliability is unimportant for constructs with formative indicators because measures examine different facets of the constructs (Petter et al., 2007, p.626).

Inevitably, constructs with formative indicators may eliminate essential items that are most likely to alter the empirical and conceptual meaning of the construct (MacKenzie et al., 2005, p.711). Another important aspect relates to the specification of a formative or reflective contrast. When constructs are specified, the entire domain of the construct must be captured because they are elements of a theory.

The nature of these components is crucial to creating effective theories (Petter et al., 2007, p.646). As a result, content validity was used to determine if the researcher used appropriate measures to capture the complete domain of the construct (Straub, Boudreau & Gefen, 2004). Furthermore, Straub et al. (2004) emphasise that content validity for reflective measures does not produce acceptable results on instrument validation. On the contrary, content validity has satisfactory results for formative constructs because they are defined by the sizes that form them (Petter et al., 2007).

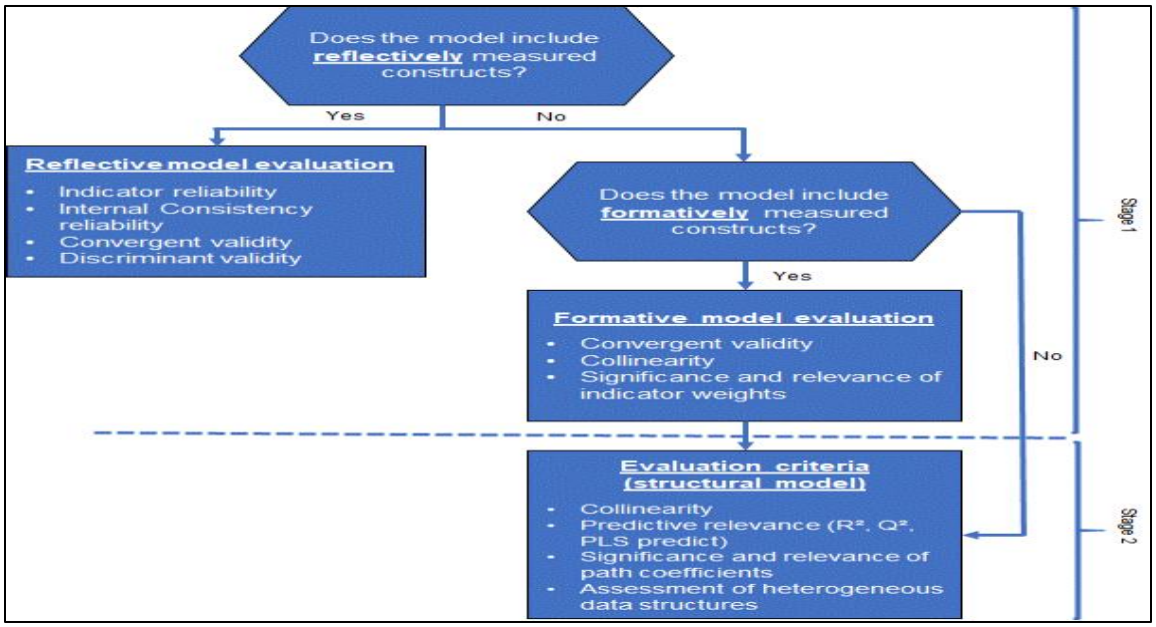
In formative models, content validity is improved by removing measures that focus on specific features of the construct (Jarvis, Mackenzie & Podsakoff, 2003). Using formative measurement models requires valid data, which shows the importance of validity in studies.

This shows that validity is vital in studies employing formative measurement models. This research involves reflective specified measurement models; therefore, latent variables were measured as reflective measures, and PLS-SEM can handle reflective specified measurement models without limitations (Becker, Rai & Rigdon, 2013; Cenfetelli & Bassellier, 2009). Petter et al. (2007, p.642) guide the reliability and validity of data before and after it was collected. This research followed the guidelines prescribed by Petter et al. (2007) to examine this study's reflective constructs.

5.9.4.2 PLS-SEM Evaluation Guidelines

This study's research model was evaluated using a two-stage PLS-SEM process depicted in Figure 5.9 below (Henseler et al., 2009). Figure 5.9 represents the researcher's process to assess the measurement and structural models in Stages 1 and 2, respectively.

Figure 5.9: PLS-SEM Evaluation Guidelines



Source: (Sarstedt et al., 2014, p.108)

This research provides support for the measurement of quality. Stage 1 and Stage 2 processes were then followed, respectively (Hair Jr, Hult, Ringle & Sarstedt, 2017a). Stage 1 examined the measurement model confirming the adequate reliability, convergent validity, and discriminant validity and verifying the research model. While Stage 2 evaluated the structural model for its predictive accuracy, the statistical significance of its path coefficients, collinearity, mediation effect, and hypothesis testing.

Goodness-of-Fit (GOF) index was assessed to validate this study's structural model. The following sections explain how this study's measurement and structural models were evaluated.

5.9.4.3 Measurement Model Evaluation (Outer Models)

The measurement model stipulates the rules of engagement between measured and latent variables. It permits researchers to use any number of variables for a single or independent construct (Hair et al., 2014a). The measurement model was appraised for this research to examine the reliability, internal consistency, and validity of this study's observed and unobserved variables.

Validity testing seeks to determine how accurately a device measures a specific notion created to assess, whereas reliability tests aim to determine the instrument's stability and consistency (Sekaran & Bougie, 2016). Validity was assessed using convergent and discriminant validity, while consistency was evaluated using single observed and construct reliability tests (Hair et al., 2012a).

According to Götz, Liehr-Gobbers and Krafft (2010), observed variable reliability quantifies the variance of an individual observed in comparison to an unobserved variable by assessing the observed variables' standardised outer loadings. Hair et al. (2012a) regard observed variables with an outer-loading of 0.700 or greater as greatly acceptable, while the outer-loadings with a value less than 0.700 should be rejected (Chin, 1998).

This research involves reflectively specified measurement constructs. Specifically, multi-item scales and indicator loadings were used to evaluate reflectively specified constructs of this study (Ringle et al., 2020). Loadings greater than 0.708 were suggested since they indicated that the construct explains more than half of the variation in the indicator, implying adequate item dependability (Hair, Risher, Sarstedt & Ringle, 2019b).

i) Internal Consistency and Reliability

In research studies, Cronbach's (1951) alpha is frequently used to evaluate a measurement item's internal consistency. In this research, Cronbach's alpha and Composite Reliability (CR) were used for internal consistency evaluation in the construct reliability. Cronbach's alpha was used to investigate the internal consistency even though it assumes comparable thresholds that generate reduced values than the reliability of composites (Yahaya et al., 2019).

Cronbach's alpha measures the internal consistency more than the reliability of an instrument, although it is less accurate because the items are unweighted (Yahaya et al., 2019). Composite reliability does not imply equivalence among the measures or that the indicators are equally weighted (Peterson & Kim, 2013).

In addition, Jöreskog's (1971) rhô-alpha was employed to measure composite reliability and overcome some of the limitations of Cronbach's alpha since it can approximately measure the PLS-SEM composites (Dijkstra & Henseler, 2015; Ringle et al., 2020).

Essentially, Jöreskog's rhô-alpha measures internal consistency reliability because composite reliability considers that indicators have different loadings. Individual reliability, which refers to various outer loadings of the indicator variables, is more important in composite reliability (Hair Jr et al., 2017a).

For this purpose, composite reliability was used since its weighted items are based on the individual loadings of the construct indicators, thus resulting in greater reliability than Cronbach's alpha coefficients (Yahaya et al., 2019). According to Nunnally (1978b), the minimum acceptable value for CR is 0.700, whereas the cut-off value for internal consistency measured by alpha is 0.700 (Cronbach, 1951).

Composite reliability has the same cut-off value as any other measure of reliability, and a score of 0.600 to 0.700 is a good sign of build reliability (Henseler & Sarstedt, 2013). As a result, any dependability estimates that are more than 0.700 but less than 0.950 are regarded as adequate (Hair Jr et al., 2017a). The scales in this research were reasonably dependable, and all the latent construct values exceeded the minimum threshold level of 0.700 in this study.

For instance, Cronbach's alpha, rhô-alpha, and composite reliability realised the internal consistency and reliability measures with values ranging from 0.842 to 0.924, 0.838 to 0.926, and 0.880 to 0.943 for Cronbach's alpha rhô-alpha, and composite reliability, respectively. The details of the analysis are presented in Chapter 6.

ii) Construct Validity

Validity refers to how well the data obtained is relevant to the research (Ghauri, Grønhaug & Strange, 2020). Validity refers to the soundness of a measure's accuracy or the amount to which a score accurately represents a notion (Zikmund et al., 2013). According to Heale and Twycross (2015, p.66), construct validity is the extent to which a research instrument measures the intended construct and permits researchers to draw inferences about test scores related to the concept studied.

Construct validity also determines how well a test's outcomes fit the ideas used to create it (Sekaran & Bougie, 2016). However, construct validity has two components: convergent and discriminant validity (Taherdoost, 2016b, p.31). Construct validity was then evaluated in terms of convergent validity and discriminant validity on the measuring scales (Sekaran & Bougie, 2016).

Convergent validity, according to Petter et al. (2007, p.641), discovers whether a concept's measurements are more associated with one another than with measures of another construct. Similarly, convergent validity is the extent to which the construct converges to explain its items' variance (Yahaya et al., 2019, p.7). This signifies that one measure of a construct correlates positively with another measure of the same construct.

The item loadings were assessed for convergent validity using the Average Variance Extracted (Hair et al., 2013). When calculating the Average Variance Extracted (AVE), the loading of each indicator on a construct must be squared and the mean value calculated (Yahaya et al., 2019, p.7). As a rule of thumb, an AVE value greater than or equal to 0.500 is acceptable (Hair et al., 2013).

An AVE of 0.500 or greater is acceptable if the construct attains an average of at least 50% of the variance of its items, thus indicating that it is explained by the construct (Chin, 1998; Yahaya et al., 2019). The AVE was calculated from each latent construct to verify the variables' convergent validity. The latent constructs absorbed the lowest 50% of the variance from the observed variables in the model. The AVE values ranged from 0.572 to 0.767, above the acceptable norm of 0.500, confirming convergent validity and good

internal consistency of the measurement model. The details of these results are provided in the next chapter.

iii) Discriminant validity

Discriminant validity is the extent to which the structural model empirically distinguishes a structure from other constructs (Yahaya et al., 2019). Meanwhile, discriminant validity concerns a construct's uniqueness or if the phenomena recorded by a construct are distinct from that captured by the other constructs in the model (Hair et al., 2013).

Discriminant validity, in essence, guarantees that an observed variable in any construct is distinguished from other constructs in the path model. It has a higher cross-loading value in the latent variable than any other construct (Sarstedt et al., 2014). Hair et al. (2012a) recommend evaluating discriminant validity using both the Fornell-Larker criteria and cross-loadings. The square root of AVE is compared to the correlation of latent constructs using the Fornell-Larker criteria (Hair Jr et al., 2017a).

According to Fornell and Larcker (1981, pp.46-47), discriminant validity is proven when a latent variable explains more variation in its associated indicator variables than it shares with other constructs in the same model. Subject to the condition that the (AVE) of each concept is equivalent to its squared correlations with other constructs in the model. The recommended requirement is that a construct should not have the same variance as any other construct whose AVE value is greater than it (Sarstedt et al., 2014).

Discriminant validity is proven when each measuring item has a weak correlation with all other constructs save the one with which it is conceptually connected (Gefen & Straub, 2005, p.92). Each indicator loading should, however, be greater than all of its cross-loadings to attain discriminant validity in PLS-SEM (Barclay, Higgins & Thompson, 1995; Chin, 1998). Consequently, the factor loading indicators associated with the assigned construct must also be higher than all loading indicators associated with other constructs, provided the cut-off value of factor loading is above 0.700 (Hair Jr et al., 2017a).

Previous research by Henseler, Ringle and Sarstedt (2015) proved that cross-loadings and the Fornell-Larcker criterion were not appropriate for evaluating discriminant validity

since they did not perform very well when all indicators loadings were between 0.650 and 0.850.

For instance, the Fornell-Larcker criterion was ineffective for discriminant validity since it relied on consistent factor loading estimates (See for example, Henseler et al., 2014; Henseler et al., 2015; Rönkkö & Evermann, 2013).

Since cross-loadings tend to overestimate indicator loadings, the Heterotrait-Monotrait Ratio of correlation (HTMT) was then recommended to evaluate discriminant validity due to its ability to achieve higher specificity and sensitivity rates of between 97 and 99 percent in comparison to 0.00 and 20.82 percentile points for the cross-loadings and Fornell-Larcker criterion respectively (Henseler et al., 2015).

The HTMT does not require factor analysis to obtain factor loadings and the calculation of construct scores (Henseler et al., 2015, p.121). Furthermore, Henseler et al. (2015) advocate that HTMT evaluates discriminant validity as a criterion involving comparing it to a predefined threshold and as a statistical test whereby hypotheses are benchmarked at confidence intervals of less than 1.00, thus indicating discriminant validity.

With high HTMT values indicating a problem with discriminant validity, Henseler et al. (2015) recommended an HTMT threshold of less than 0.900 for path models with conceptually similar constructs and a 0.850 threshold for path models are conceptually more distinct.

Meanwhile, HTMT values higher than this threshold points to a conclusion that there is a lack of discriminant validity. For this purpose, the HTMT was used to evaluate the discriminant validity instead of the Fornell-Larker and cross-loadings (Ringle et al., 2020, p.10). The recommended threshold criterion of less than 0.900 was used to compare discriminant validity for this research.

Bootstrapping procedures were additionally performed to achieve discriminant validity within the HTMT values lower than one for statistically significance and permitted confidence intervals to be constructed to allowed for HTMT (Henseler et al., 2016; Henseler et al., 2015).

In this research, all the HTMT values among the related constructs are within the acceptable criterion of less than 0.900, thereby confirming discriminant validity except for the correlation between information accuracy and information usefulness and showing the HTMT value of 0.925 which is above the benchmark and concluding lack of discriminant validity. The measurement model evaluation thus confirmed the convergent validity and acceptable internal consistency. A valid HTMT model was also found in this study for measuring discriminant validity.

5.9.4.4 Structural Model Evaluation

The structural model is analysed after successfully validating the measurement model (Chin, 1998; Ringle et al., 2020). In this research, the assessment of the measurement model was satisfactory. Therefore, the structural model validation systematically assessed whether this study's hypothesis were supported by the research data (Urbach & Ahlemann, 2010).

This research appraised collinearity, the overall fit of the estimated model, the statistical significance and relevance of the path coefficients (ß value) and T-statistic value, the effect size (f^2), the coefficient of determination (R^2), the predictive relevance of the model (Q^2) (Benitez, Henseler, Castillo & Schuberth, 2020; Dijkstra & Henseler, 2015; Henseler et al., 2014; Yahaya et al.,2019). The index for the complete model fit the Goodness-of-Fit (GOF) was also employed to ensure that the model was verified and adequately explained the empirical data (Tenenhaus et al., 2005).

i) Collinearity

Although common method bias can still be contaminated, the model can pass the criterion for acceptable convergent and discriminant validity (Kock, 2015). It was then critical to assess the non-independence of predictor variables discovered in this study's regression-type analysis, which inflates the variance of regression parameters, potentially leading to the incorrect identification of relevant predictors in a statistical model; while also creating collinearity (Dormann et al., 2013, p.27). Collinearity describes the situation where two or more predictor variables in a statistical model are directly related (Alin, 2010).

Collinearity is achieved when more than two predictors measure the same underlying construct or facets of such construct (Kock, 2015, p.7). According to Kock (2015,p.5), cumulative latent variable indicators include common variation, susceptibility to increased collinearity levels among the latent variables, and consequential inflated path coefficients.

This research tested vertical and lateral collinearity among the latent variables (Kock & Lynn, 2012). Multiple regression of each indicator in the measurement model was used to determine the item's Variance Inflation Factor (Sarstedt et al., 2017). The multicollinearity indicator's Variance Inflation Factor (VIF) value less than 5 confirms that the model is free from pathological collinearity (Hair et al., 2011).

The outer VIF values ranged between 2.003 to 3.103 for all variables, including control variables which are lower than the threshold of 5.00, indicating no model-wide multicollinearity, thus confirmative that the research model is free from common method bias (Cenfetelli & Bassellier, 2009; Kock & Lynn, 2012; Petter et al., 2007). The inner VIF only showed collinearity issues between information accuracy and CIE paths along with information credibility and CIE. At the same time, multicollinearity was not found in most variables. The full details are presented in Chapter 6.

ii) Goodness of Fit

PLS-SEM model fit measures were recommended by Henseler et al. (2016). Researchers must be very cautious when evaluating these measures in PLS-SEM (Henseler and Sarstedt, 2013; Hair et al., 2019c).

This research employed the Standardized Root Mean Square Residual (SRMR), the Root Mean Square residual covariance (RMS_theta), the Normed Fit Index (NFI), Goodness-of-Fit (GOF) index, and the exact model fit to estimate the model fit test (Dijkstra & Henseler, 2015; Henseler et al., 2014). Hair et al. (2014b) established SRMR goodness of fit metrics for PLS-SEM to avoid model misspecification.

The SRMR measures how similar the observed and predicted covariance matrices are in standardised residuals (Chen, 2007). The SRMR measures the estimated model fit (Hussain, Fangweni, Siddiqi, Ali & Shabbir, 2018; Yahaya et al.,2019).

The SRMR threshold values range from zero to one, with well-fitting models achieving a value of less than 0.050 (Byrne, 1998; Diamantopoulos & Siguaw, 2000). Hu and Bentler (1998) advise that an SRMR threshold of less than or equal to 0.080 indicates a satisfactory match for the research model. A good match is also defined as an SRMR score of less than 0.100 or 0.080 in a more cautious variant (Hu & Bentler, 1999).

With these differing views, Benitez et al. (2020, p. 5) caution that the suggested SRMR threshold and discrepancy measures are still preliminary, pointing to more detail in future research. This study's SRMR values for the estimated and the saturated models were 0.055 and 0.078, respectively, which are acceptable and a good fit (Hu and Bentler, 1999).

Additionally, the GOF index was measured as 0.656 and 0.652 for both the R^2 and the adjusted R^2, thereby indicating that the model had a substantial predictive power compared. In this reflectively measured construct model, the outer model residuals—the RMS_theta, representing the root mean square residual covariance matrix was employed as a fitness measure for the structural model (Lohmöller, 1989).

An RMS-theta value below 0.120 indicates a well-fitting model, while a high value indicates a poor fit (Hair et al., 2014b). This research's RMS_theta value was 0.101, indicating a well-fitting model (See the next chapter for details). The NFI is an incremental fit metric that calculates the proposed model's Chi-square value and compares it to a suitable benchmark (Bentler & Bonett, 1980). For this research, NFI fit index values vary from 0.000 to 1.00, with 1.00 suggesting a better match (Schermelleh-Engel, Moosbrugger & Müller, 2003, p.40).

Schermelleh-Engel et al. (2003) advocate that NFI values equal 1.00, and that the target model is the best feasible improvement over the independence model. Even if the stated model is valid, an NFI result may not approach the top limit of 1.00, especially in smaller samples (Bentler, 1990, p.239). Bentler and Bonett (1980) recommended NFI values greater than 0.900, indicating a good fit. In contrast, the rule of thumb suggests NFI values equal to 0.950 as a gauge of good fit relative to the baseline model (Kaplan, 2000, p.107).

Equally, an NFI criterion greater than or equal to 0.950 was suggested (Hu & Bentler, 1999). NFI values above 0.900 usually represent an acceptable fit (Marsh & Grayson, 1995; Schumacher & Lomax, 1996).

Importantly, the NFI represents an incremental fit measure and does not penalise model complexity (Hooper et al., 2008). This complex research model resulted in the NFI for the saturated and estimated model attaining 0.715 and 0.709, respectively, which is less than the required benchmark of 0.900. This shows that the NFI index is subtle to the sample size (Bentler, 1990; Mulaik, James, Van Alstine, Bennet, Lind & Stilwell, 1989).

NFI was not exclusively relied on to estimate model fit for this research (Kline, 2005a). Researchers should use NFI with caution for model comparison because it does not penalise adding parameters. In addition, NFI thresholds for composite models are still to be determined by future research (Henseler et al., 2016, p.10).

iii) Statistical Significance and Predictive Relevance of the Model

Aguirre-Urreta and Rönkkö (2018) suggested that researchers examine the indicator weights' significance and relevance. This study employed bootstrapping to generate p values and the Bias-Corrected and Accelerated (BCa) confidence intervals. This research has drawn 5000 bootstrap samples for the final analysis (Streukens & Leroi-Werelds, 2016).

A bootstrap procedure with a resample of 5,000 evaluated the models' path coefficients β value and the corresponding T-statistic along with estimating R^2 values of the endogenous constructs to measure the model predictive power along with the models' s predictive relevance (Q^2) as well as its effective sizes (f^2) (Hair Jr et al., 2017a; Ringle et al., 2020).

For standardised paths to be meaningful for discussion, Chin (1998) argues that they must be at least 0.200 and ideally over 0.300. A standardised path coefficient ranging from -1.00 to +1.00 was used to test the statistical significance and strength of the causal relationships (Hair et al., 2019b). This β value was employed to test the significance of

the hypothesis. In so doing, the β values of the paths in the hypothesised model were calculated.

Consequently, T-statistic tests were employed to verify the significance level of the β (Hussain et al., 2018; Yahaya et al., 2019). Additionally, the bootstrapping procedure was used to evaluate the significance of the hypothesis (Chin, 1998).

The path coefficient and T-statistics values were examined for their importance. A bootstrapping technique was carried out on 5000 subsamples with no sign changes (Hussain et al., 2018; Yahaya et al., 2019). Meanwhile, bootstrapping was drawn from many subsamples from the original data with replacements (Ringle et al., 2020; Sarstedt et al., 2017).

This process permitted the researcher to construct parameters under investigation and compute bootstraps standard errors that allowed to calculate T-statistics values and corresponding p- values in establishing the statistical significance of original indicator weights (Sarstedt et al., 2017).

Yahaya et al. (2019, p. 11) explain statistical significance as being different from zero at a 5% significance level when the p-value is below 0.050. They also propose that confidence intervals constructed around the estimate do not include zero. This research employed t-values of 1.960 for a two-tailed test with the corresponding p-value less than 0.050 at a 5% significance level (Hair Jr et al., 2017a).

Based on α of 0.050, the test statistic generated from the path coefficients should be greater than ± 1.960 to accept or reject the hypothesis. This research found significance with p-values less than 0.050 in line with the corresponding T-Statistics above 1.960 (Please refer to Chapter 6 for more details).

The p-value establishes the effect's existence, although it does not reveal the impact of the size, which is the degree of the effect of each exogenous latent construct on the endogenous latent construct. Both the substantive significance effect size (f^2) and statistical significance (p-value) were reported in this research study (Sullivan & Feinn, 2012, p.279).

An effect size can be seen as a measure of an effect when the sample size is not considered (Benitez et al., 2020, p.11). The f^2 threshold values of 0.350, 0.150, and 0,020 indicate strong, moderate, and weak effects (Benitez et al., 2020, p. 12; Cohen, 1988).

The effect size for CIE on CS and OP, CS on OP and ERC on OP were 1.023, 0.111, 0,198 and 0.305, respectively, thus suggesting a moderate effect (see Chapter 6 for more details). The cumulative f^2 of all thirteen exogenous constructs on CIE had a weak impact on the value of its R^2, whereas the f^2 of the mediating, moderating, and exogenous constructs on organisational performance had a moderate effect on the value of the R^2 (Cohen, 1988). In this research, significance was found between the constructs CIE and CS, CIE and OP, CS and OP, ERC and CIE, employee and CIE, as well as strategy and CIE.

iv) Explanatory Power

For the structural model, the R^2 evaluates the total effect size, and variation explained in the endogenous construct (Yahaya et al., 2019, p.22). As a result, the R^2 is a metric for in-sample predictive power (Rigdon, 2016; Sarstedt et al., 2017). The R^2 value spans from 0.000 to 1.00, with higher values suggesting greater predictability and explanatory power (Hair Jr et al., 2017a; Hair et al., 2019b).

The R^2 of the structural model's endogenous construct measures the total effect size and variation explained (Yahaya et al., 2019, p.22). In summary, the R^2 measures the predictive power of an in-sample model (Rigdon, 2016; Sarstedt et al., 2017). The R^2 value varies from 0.000 to 1.00, with higher values suggesting better prediction and explanatory power (Hair Jr et al., 2017a; Hair et al., 2019b). The rule of thumb for R^2 suggests that values of 0.250, 0.500, and 0.750 are weak, moderate, and strong (Hair et al., 2011).

R^2 values of 0.750, 0.500, and 0.260 are thus considered substantial, moderate, and weak, respectively (Hair et al., 2013; Henseler et al., 2009). In the current study, the R^2 values were 0.615, 0.506, and 0.735 for CIE, CS, and OP, collectively considered moderately strong (See Chapter 6 for more details).

This study's inner path models were 0.615, 0.506, and 0.735 for CIE, CS, and OP endogenous latent constructs. This signifies that 61.5% change in CIE was due to thirteen latent constructs in the model, while 50.60% of the variation in CS was ascribed to the mediating construct CIE. Additionally, the variance of 73.50% in OP was the consequence of the mediating (CIE), moderating (CS), and the exogenous variable (ERC).

v) Predictive Relevance of the Model

Ringle et al. (2020,p.11) point out that researchers need to evaluate the model's predictive power once the statistical significance of the model is completed. This research employed predictive performance to strengthen the validity of the statistical model fit (Woodside, 2013). The Q^2 value is a metric used to evaluate the path model's predictive accuracy (Geisser, 1974; Stone, 1974).

According to Hussain et al. (2018,p.15), the Q^2 criterion validates that the structural model predicts endogenous latent constructs. Q^2 values larger than 0.000 for specific endogenous show an indicative predictive accuracy for that particular construct (Hussain et al., 2018; Yahaya et al., 2019). Notably, Q^2 values greater than 0.000 indicate that the model can predict a specific endogenous component. On the other hand, values of 0.000 and lower show a lack of predictive usefulness (Hair et al., 2019b; Hair Jr et al., 2017a).

The rules of thumb suggest Q^2 higher than 0.000,0.250, and 0.500 to depict small, medium and large predictive relevance for PLS path models (Chin, 1998). The rules of thumb do not yet consider the Q^2's sampling distribution, but they point to the magnitude prediction errors (Shmueli, Ray, Estrada & Chatla, 2016, p.4557). The Q^2 is calculated to measure either the predictive communality or redundancy in PLS models (Shmueli et al., 2016, p.4557).

Meanwhile, Q^2 statistics measures predictive validity through blindfolding procedures (Chin, 2010; Evermann & Tate, 2012; Tenenhaus, Vinzi, Chatelin & Lauro, 2005). The blindfolding process excludes a part of the data matrix, estimates the model parameters, and predicts the previously computed estimates to calculate Q^2 statistics (Ringle et al., 2020).

The Q^2 combines aspects of out-of-sample prediction with explanatory power (Shmueli et al., 2016; Sarstedt et al., 2017). This research combined the in-sample and out-of-sample predictions to assess the model's predictive performance. Blindfolding procedures and cross-validation redundancy were then used to calculate the Q^2 (Geisser, 1974; Stone, 1974; Tenenhaus et al., 2005).

Q^2 values higher than 0.000, 0.250, and 0.500 depict small, medium, and large predictive relevance, respectively (Hair et al., 2019b, p.12). This study's blindfolding and cross-validation redundancy measures showed Q^2 values of 0.441, 0.343, and 0.443 for CIE, CS, and OP, respectively, which were greater than 0.000, indicative of the exogenous constructs having predictive importance for the endogenous constructs (Hair Jr et al., 2017a).

The Mean Absolute Error (MAE), which represents the average size of the mistakes, and the Root Mean Squared Error (RMSE) were generated to quantify the degree of prediction error using the PLSpredict-based assessment of a model's predictive capacity (Shmueli et al., 2016). Instead of assessing the prediction errors for all endogenous constructions' indicators, this study evaluated PLSpredict findings based on the model's core endogenous construct (Hair et al., 2019b).

According to Hair et al. (2019b), $Q^2\_predict$ values greater than 0.000 shows that the model outperforms the naïve benchmark. This study's $Q^2\_predict$ values were therefore positive and above 0.000, thus indicating the model's predictive accuracy. The details are provided in Chapter 6.

5.10 Ethical Considerations

The term "ethics" refers to broad principles and norms that deal with moral issues (Wiles, 2012). As a result, ethics refers to the branch of study that determines what behaviours are proper in specific situations, as mandated by societal norms of ethical conduct (Burns & Bush, 2010). So, ethical oversight protects the researcher and participants involved in a research study (George, 2016, p.2).

Therefore, research ethics concern moral behaviour in a research context (Wiles, 2012, p.4). This shows that research ethics involves doing what is morally and legally right in research. Kara (2018, p.9) points out that ethical research in the real requires an ongoing and active engagement with people and the environment around them. Essentially, research cannot be ethically qualified by completing a once-off task.

Consequently, researchers must work diligently and ethically throughout the research process (Kara, 2018, p.9). This validates that ethics play a vital role in the research process and thereby remain essential for researchers.

With research activities involving obtaining data from human beings and organisations as objects of study, processing research data and distributing the study findings lead to ethical considerations before a research activity commences (Anwar, 2016). It is vital for researchers to be trustworthy as well as address various ethical concerns and issues at different levels of the research process (Bickman & Rog, 2008).

Trust aids the credibility and objectivity of research results, enhancing the quality and relevance of the research project (Roloff & Zyphur, 2018). The norms also promote the research aims, such as knowledge, truth, and error avoidance. In a study involving human participants, ethical issues exist, resulting in ethical dilemmas in research (Zikmund et al., 2013).

Researchers must be cautious and treat each case discrete and be aware of issues of sensitivity of the respondents before undertaking research. Furthermore, the researcher should allow respondents the flexibility to withdraw their participation at any instant during the research study (Bryman & Bell,2015).

For this reason, the researcher considered different ethical issues and was conversant with the rules that may affect the outcome of the research at an early stage before commencing his research activities (Collis & Hussey, 2013). The researcher practised the ethical idealist principles by ensuring that each participant read and signed informed consent before undertaking the research activities.

Based on the University of KwaZulu-Natal's (UKZN's) guidelines on ethical considerations when collecting data, the researcher certified that the safety of participants was not compromised in any way, and the nature of this study was disclosed to the participants in writing as part of the research questionnaires.

All participants were informed of their rights to withdraw from the study at any time if they choose to, and their participation in this research was voluntary. The researcher ensured the confidentiality and anonymity of all participants were guaranteed at all stages of the research process.

In this manner, all participants could not be identified with any of their opinions during and after the research process. Because participants may answer the questionnaire honestly, this practice was crucial to the research validity. Other ethical considerations addressed in this study were the researcher's role following the data gathering technique, particularly during the data analysis stage (Sekaran & Bougie, 2016).

Additionally, all research participants were provided with a cover letter that included the title, purpose, and impact of the study and the estimated time to complete the questionnaire. The cover letter included the contact details of the researcher and supervisor and UKZN's details for easy enquiry regarding the ethical elements of this research (See Appendix A). Importantly, ethical clearance was obtained from the UKZN before the data collection stage (see Appendix E). Furthermore, the researcher adhered to the ethical codes of the UKZN.

5.11 Conclusion

This chapter's primary goal was to provide and defend the philosophical viewpoints, methodologies, procedures, and statistical techniques employed to meet the study's research objectives. Quantitative approaches were used in this work to examine and validate potential links between the elements of the conceptual model. An online survey method guided by the positivism paradigm was employed in which a structured-administered questionnaire uploaded on Google Drive's Form website was used to collect

quantitative data for this research project. Cronbach's alpha was also employed to assess the questionnaire item's reliability.

A probability sampling was employed to select respondents for this study. Furthermore, a simple random sampling eliminated any preferences and avoided bias or lack of representativity. The research employed SPSS version 24.0 to produce descriptive and inferential statistics, while PLS-SEM using SmartPLS software 3.3.3 was used to test complex relationships amid variables, including many hypotheses simultaneously.

The researcher explained why this approach was chosen and the intricacy of the conceptual model. This study's measurement and structural models were evaluated using a two-stage approach. The ethical issues followed during the inquiry, particularly during data collecting, were also discussed in this chapter.

The chapter also explained ethical considerations followed during the investigation, especially during data collection. The data analysis findings are presented, interpreted, and discussed in the next chapter.

Chapter Six: Analysis and Presentation of Results

6.1 Introduction

The preliminary and in-depth statistical examination of the correlations among the components within the proposed study model is presented in this chapter. For primary data analysis, including data screening, frequencies, and percentages, and to assess the reliability of the questionnaire questions in this study, SPSS version 24.0 was used. The findings of the descriptive statistics are presented first in this chapter. The descriptive statistics for the sample, the profiles of the individuals, and the mean scores for their replies are all reported.

The descriptive statistics of the measuring items and the constructs are presented. The reliability test findings using Cronbach's alpha are then reported, followed by inferential statistics presented in tables and formulae. To analyse the conceptual study model, SEM utilised the software program Smart Partial Least Squares (SmartPLS 3.2.7).

Also, PLS-SEM was employed to perform explanatory and predictive analysis, and a two-stage procedure for evaluating this study's measurement and structural models is presented in this chapter.

The presentation of the results in this chapter is outlined. Firstly, the analytical sample is described, and the sample's demographic data are summarised using frequencies and proportions. Secondly, an analysis overview of the constructs and measurement scales is presented by reporting validity and reliability measurement results, including median values for each measurement scale.

Cronbach's alpha values for each construct, indicator loading scores for each construct, internal consistency reliability, and composite reliability are also included. Finally, all tests for the hypotheses and their results are presented. This chapter also indicates how the hypothesis was tested through PLS-SEM using path analysis to assess associations and mediation between latent constructs. Additionally, model validity measures are reported.

6.2 Descriptive Statistics

Preliminary data analysis was done in the previous chapter to confirm that the assumpti ons of normality, linearity, and multicollinearity were not violated. In addition, a screening process that involved examining missing data, unengaged responses, and outliers was conducted.

The median of nearby points in SPSS version 24.0 replaced missing data. The descriptive tables and box plots retrieved from the SPSS version 24.0 output assisted in detecting and handling outliers. After the data cleaning and screening process, the final sample size for this research was 276. Descriptive statistics were used to summarise observations (Mishra et al., 2019).

The descriptive statistics acquired from the 276 sample characteristics are shown in the next section. The descriptive statistics, measuring items, and their relevant constructs are reported, as well as the Cronbach alpha values derived for item reliability.

6.2.1 Response Rate

The questionnaire was distributed to 384 participants, of which a total of 280 participants responded to the survey, and a 73 percent response rate was achieved. Four respondents were excluded from the sample because they did not meet the study's inclusion criteria of being currently employed, thus resulting in a final analytic sample of 276 respondents.

6.2.2 Demographic Profile of the Respondents

Respondents were requested to submit biographical information in section A of the questionnaire. SPSS version 24.0 was used to analyse and generate information about respondents' gender, age group, racial group, highest education level, and occupation level (See Table 6.1 below).

Table 6.1: Demographic Characteristics of the Sample

Descriptive Statistics	N=276	Percentage (%)
Demographics		
Gender		
Male	137	49.6
Female	138	50.0
Other	1	0.4
Age Group		
18 -25 years old	7	2.5
26 - 35 years old	58	21.0
36 - 45 years old	89	32.2
46 - 55 years old	94	34.1
56 - 65 years old	25	9.1
66 years old and above	3	1.1
Ethnicity		
White	121	43.8
Black	102	37.0
Coloured	20	7.2
Indian	30	10.9
Other	3	1.1
Educational Level		
Matric	45	16.3
Diploma	55	19.9
Undergraduate Degree	44	15.9
Postgraduate Degree	117	42.4
Other	14	5.1
Marital Status		
Single	68	24.6
Married	172	62.3
Widowed	5	1.8
Divorced	28	10.1
Separated	3	1.1
Employment Status		
Are you currently employed?		
Yes	276	100
No	0	0
Employment position		
Junior Management	25	9.1
Middle Management	60	21.7
Professional Qualified Experienced Specialist	60	21.7
Senior Management	39	14.1
Specialist	67	24.3
Top Management/ Executive Management	25	9.1

Table 6.1 discloses that 138(50%) respondents were females while 137(49.6%) were male, and 1(0.4%) respondent did not disclose any gender. This result shows willingness, mostly from female respondents, to participate in the study. Furthermore, the results from Table 6.1 have demonstrated that 94 (34.1%) of the respondents were aged between 46 and 55 and 89 (32.2%) were aged 36 and 45. In addition, 58 (21.0%) were aged between 26 and 35, while 25 (9.1%) were aged between 56 and 65, and 7(2.5%) of the

respondents were between 18 and 25 years. Another 3 (1.1%) of the respondents indicated 66 years and above as their age group. This result demonstrates that middle-aged adults still dominate the insurance industry. Yet, the industry is moving towards digitalisation.

Additionally, 172 (62.3%) of the respondents indicated that they were married, whereas 68 (24.6%), 28 (10.1%), 5 (1.8%), and 3 (1.1%) indicated that they were either single, divorced, widowed, and separated respectively. Equally, the results in Table 6.1 showed that 121(43.8%) and 102 (37%) respondents from white and black ethnic groups participated in this research, while 30 (10.9%), 20 (7.2%), and 3 (1.1%) respondents were respectively from Indian, Coloured and Other ethnic groups. This result signifies the representation of ethnic groups in the life insurance industry.

Respondents were also asked to state their educational level. According to the study findings, 117 (42.4%) respondents completed post-graduate degrees, followed by 55 (19.9%), 45 (16.3%), 44 (15.9%), and 14 (5.1%) of the respondents who have completed diplomas, matric, undergraduate degrees, and another form of qualification respectively. This result indicates that all surveyed participants understood the effect of competitive intelligence embeddedness' and customer satisfaction on organisational performance.

These results also indicate that the life insurance industry is characterised by intense competition, information, and knowledge; hence, most employees in this sector have qualifications higher than matric. Age, gender, marital status, ethnic origin, and the highest level of completed education, on the other hand, are linked to a reduced non-response rate (Christensen, Ekholm, Glümer & Juel, 2013).

In terms of the level of occupation, Table 6.2 indicates that 67 (24.3%) of the employees in specialist roles participated more in this survey. Another 60 (21.7%) and 60 (21.7%) of the employees were in the specialist role middle management and professionally qualified experience specialist roles, respectively, while 39 (14.1%) of the employees were in senior management roles. In addition, 25 (9.1%) and 25 (9.1%) of the top management and junior management roles participated in this study.

6.2.3 Mean and Standard Deviation of Constructs

This research employed a five-point Likert scale rating per item within each construct, and the respondent's level of agreement with each of the statements was measured on a five-point Likert scale whereby [1] = Strongly disagree; [2] =Disagree; [3] = Neutral; [4] Agree; [5] = Strongly agree. The average scores per item by construct are reported in Table 6.2 below. This study's descriptive statistics showed that all the constructs had a mean above the mid-point of 3.000 out of 5.000, thus indicating that respondents agreed with the statements.

6.2.3.1 Organisational Factors

The organisational factors impacting CIE are leadership, strategy, structure, process, and employees. On a five-point scale, the descriptive statistics of the organisational factors were rated. The average mean values for the organisational factors ranged from 3.144 to 3.838 and were above the mid-point of 3.000 out of 5.000, indicating average to high motivational levels. In tandem, the standard deviation ranged from 0.831 to 1.038, demonstrating that the respondents somewhat agreed with the statements (Please refer to Table 6.2 below).

i) Leadership

The questionnaire contained six attitude-measuring questions with a five-point Likert scale rating in which respondents reflected their opinions about how they perceived leadership support on CIE. The mean values of the items ranged from 3.337 to 3.728, above the mid-point of 3.000 out of 5.000. This result suggests average to high motivational levels, while the marginal performance of the standard deviation ranged from 1.727 to 1.787, thus implying that data is very close in value to the mean.

The overall leadership mean was 3.572, indicating a high motivational level and an acceptable standard deviation of 0.985. This result shows that 71.44% of the respondents agreed to some extent with the statements, while 28.56% responded differently (See Table 6.2 below).

ii) Strategy

The six-worded questions assessed respondents' impressions of the impact of strategy on CIE using a five-point Likert scale rating system. The mean values of the items ranged from 3.580 to 3.971, above the mid-point of 3.000 out of 5.000. This result shows a high motivational level. The acceptable standard deviation ranged from 0.767 to 0.956, suggesting that the data was very close in value to the mean.

The overall strategy mean score was 3.838, indicating a high motivational level and an acceptable standard deviation of 0.831. This result signifies that 76.76% of the respondents agreed with the statements, whereas 23.23 % responded differently (see Table 6.2 below).

iii) Structure and Process

The effect of structure and process on CIE was measured with a five-point Likert scale rating where respondents indicated their perceptions regarding the six-worded statements. The mean values of the items ranged from 3.087 to 3.522, above the mid-point of 3.000 out of 5.000. This result indicates average to high motivational levels, while the acceptable standard deviation ranged from 0.963 to 1.068, suggesting that data was very close in value to the mean.

The overall structure and process mean was 3.353, indicating a high motivational level and an acceptable standard deviation of 1.004, respectively. This result shows that 67.06% of the respondents fairly agreed with the statements, whilst 32.94% responded otherwise (See Table 6.2 below).

iv) Employee Capability

A five-point Likert scale was used to answer six written statements in the questionnaire, which was aimed to gauge respondents' impressions of how employee capabilities are considered to utilise CIE. The mean values of the items ranged from 3.072 to 3.272, which were above the mid-point of 3.000 out of 5.000. This result indicates an average motivational level.

In tandem, the acceptable standard deviation ranged from 0.985 to 1.100, indicating that the data was very close in value to the mean. The overall structure and process mean of 3.144 shows an average motivational level and an acceptable standard deviation of 1.038. This result signifies that 62.88% of the respondents were uncertain about the impact of the effect of employees on CIE. As such, they had marginally agreed with the statements. In comparison, 37.12% of the respondents responded differently to this statement (See Table 6.2 below).

6.2.3.2 Market Factors

The market factors, competition, customers, technology, and information providers influence CIE. A five-point rating scale was used to measure these market factors. The average mean values for these market factors ranged from 3.362 to 3.775 and stood above the mid-point of 3.000 out of 5.000. This result indicates an average to high motivational level.

At the same time, the acceptable standard deviations ranged from 0.895 to 0.974, respectively. This result implies that the respondents partially agreed with the statements (See Table 6.2 below).

i) Competition

The impact of competition on CIE was measured with a five-point Likert scale rating where respondents indicated their perceptions regarding the five-worded statements. The mean values of the items ranged from 3.312 to 4.261, above the mid-point of 3.000 out of 5.000.

This result shows an average to high motivational level, whereas the acceptable standard deviation ranged from 0.901 to 1.047, indicating that the data was very close in value to the mean.

The overall mean of the competition was 3.615 showing a high motivational level and an acceptable standard deviation of 0.974, respectively. This result suggests that 72.30% of the respondents reasonably agreed with the statements, while 27.70% responded differently (See Table 6.2 below).

ii) Customer Insights

The five-worded questions were developed to assess respondents' impressions of the impact of customer insights on CIE using a five-point Likert scale rating system. The items' mean values ranged from 3.685 to 3.862, above the mid-point of 3.000 out of 5.000.

This result indicates a high motivational level. The acceptable standard deviation ranged from 0.863 to 0.941, illustrating that data was very close in value to the mean. The customer's overall mean was 3.775, indicating a high motivational level and an acceptable standard deviation of 0.906. This result exemplifies that 75.50% of respondents moderately agreed with the statements while 24.50 responded differently (See Table 6.2 below).

iii) Technology

The purpose of the survey was to gauge respondents' opinions on the impact of technology on CIE. A five-point Likert scale was applied to answer five-word statements. The mean values of the items ranged from 3.167 to 3.630, above the mid-point of 3.000 out of 5.000. This result indicates an average to high motivational level, whereas the acceptable standard deviation ranged from 0.903 to 1.132, proving that data was very close in value to the mean.

The technology's overall mean was 3.362, showing an average motivational level and an acceptable standard deviation of 1.013, respectively. Meanwhile, 67.24% of the respondents discreetly agreed with the statements, whereas 32.76% disagreed (See Table 6.2 below).

iv) Information Providers

The influence of information providers on CIE was measured with five-worded statements in which a five-point Likert scale was employed. The mean values of the items ranged from 3.159 to 3.594, above the mid-point of 3.000 out of 5.000. This result demonstrates an average to high motivational levels, whereas the standard deviation ranged from 0.850 to 0.978, thus attesting that data was very close in value to the mean.

The overall information providers mean of 3.456 indicates an average motivational level and an acceptable standard of 0.895, respectively. This result demonstrates that 69.12% of the respondents modestly agreed with the statements, whilst 30.88 disagreed (See Table 6.2 below).

Table 6.2: Mean and Standard Deviation of Constructs

Main Constructs	Items	Observations	Mean Scores		STD. DEV		Items Cronbach's α
Organisational Factors							
Leadership	L1	276	3,728	3,572	0,985	0,985	0,881
	L2	276	3,641		0,960		
	L3	276	3,652		0,966		
	L4	276	3,388		1,030		
	L5	276	3,337		1,026		
	L6	276	3,688		0,940		
Strategy	STRA1	276	3,964	3,838	0,781	0,831	0,906
	STRA2	276	3,938		0,767		
	STRA3	276	3,580		0,956		
	STRA4	276	3,699		0,895		
	STRA5	276	3,877		0,818		
	STRA6	276	3,971		0,767		
Structure & Process	SP1	276	3,337	3,353	1,068	1,004	0,902
	SP2	276	3,384		0,963		
	SP3	276	3,087		1,030		
	SP4	276	3,377		1,018		
	SP5	276	3,413		0,978		
	SP6	276	3,522		0,966		
Employee	E1	276	3,072	3,144	1,100	1,038	0,903
	E2	276	3,141		1,022		
	E3	276	3,257		0,985		
	E4	276	3,272		0,996		
	E5	276	3,014		1,041		
	E6	276	3,105		1,082		
Market Factors							
Competition	CP1	276	4,261	3,615	0,901	0,974	0,892
	CP2	276	3,312		1,047		
	CP3	276	3,322		1,027		
	CP4	276	3,630		0,935		
	CP5	276	3,551		0,960		
Customer	C1	276	3,779	3,775	0,925	0,906	0,908
	C2	276	3,685		0,941		
	C3	276	3,688		0,893		
	C4	276	3,862		0,863		
	C5	276	3,859		0,906		
Technology	T1	276	3,167	3,362	1,132	1,013	0,896
	T2	276	3,388		1,019		
	T3	276	3,630		0,903		
	T4	276	3,330		1,039		
	T5	276	3,293		0,971		
Information Providers	IP1	276	3,580	3,456	0,872	0,895	0,898
	IP2	276	3,159		0,978		
	IP3	276	3,428		0,881		
	IP4	276	3,518		0,896		
	IP5	276	3,594		0,850		
Information Attributes							
Information Quality	IQ1	276	3,562	3,668	0,957	0,911	0,923
	IQ2	276	3,649		0,940		
	IQ3	276	3,681		0,902		
	IQ4	276	3,714		0,858		
	IQ5	276	3,736		0,898		
Information Credibility	IC1	276	3,714	3,819	0,883	0,833	0,921
	IC2	276	3,768		0,807		
	IC3	276	3,855		0,849		
	IC4	276	3,902		0,819		
	IC5	276	3,855		0,809		
Information Accuracy	IA1	276	3,676	3,617	0,855	0,909	0,922
	IA2	276	3,707		0,889		
	IA3	276	3,685		0,933		
	IA4	276	3,406		0,981		
	IA5	276	3,609		0,886		
Information Usefulness	IU1	276	3,812	3,681	0,777	0,898	0,901
	IU2	276	3,489		1,011		
	IU3	276	3,620		0,944		
	IU4	276	3,681		0,886		
	IU5	276	3,804		0,873		
Employee Role Clarity							
Employee Role Clarity	ERC1	276	3,185	3,401	1,121	1,025	0,827
	ERC2	276	3,239		1,055		
	ERC3	276	3,496		1,007		
	ERC4	276	3,746		0,911		
	ERC5	276	3,337		1,030		
Customer Satisfaction							
Customer Satisfaction	CS1	276	3,685	3,764	0,889	0,836	0,886
	CS2	276	3,808		0,815		
	CS3	276	3,703		0,886		
	CS4	276	3,848		0,799		
	CS5	276	3,775		0,791		
Organisational Performance							
Organisational Performance	OP1	276	3,714	3,552	0,858	0,894	0,878
	OP2	276	3,236		0,998		
	OP3	276	3,471		0,947		
	OP4	276	3,620		0,838		
	OP5	276	3,721		0,830		
Competitive Intelligence Embeddeness							
Competitive Intelligence Embeddeness	CIE1	276	4,029	3,912	0,786	0,818	0,916
	CIE2	276	3,967		0,811		
	CIE3	276	3,804		0,847		
	CIE4	276	3,917		0,820		
	CIE5	276	3,844		0,827		

6.2.3.3 Information Attributes

The proposed information attributes having a bearing on CIE involve information accuracy, credibility, quality, and usefulness. The descriptive statistics for the information attributes were measured on a five-point scale rating. The average mean values for the information attributes ranged from 3.617 to 3.819 and above the mid-point of 3.000 out of 5.000. This result indicates a high motivational level. At the same time, the acceptable standard deviations ranged from 0.833 to 0.911. This result implies that respondents agreed with the statements (See Table 6.2 above).

i) Information Quality

The purpose of the survey was to determine how respondents felt about the impact of information quality on CIE, wherein a five-point Likert scale was applied to answer five-worded statements. The mean values of the items ranged from 3.562 to 3.736, above the mid-point of 3.000 out of 5.000. This result shows a high motivational level, whereas the acceptable standard deviation ranged from 0.858 to 0.957, verifying that data was very close in value to the mean.

The overall information quality mean was 3.668, indicating a high motivational level and an acceptable standard deviation of 0.911, respectively. This result suggests that 73.36% of the respondents moderately agreed with the statements, whereas 26.64% disagreed (See Table 6.2 above).

ii) Information Credibility

The five-worded questions assessed respondents' impressions of the influence of information credibility on CIE using a five-point Likert scale rating system. The mean values of the items ranged from 3.714 to 3.902, above the mid-point of 3.000 out of 5.000.

This result demonstrates a high motivational level. The standard deviation ranged from 0.807 to 0.833, illustrating that data was very close in value to the mean. The overall information credibility mean was 3.819, indicating a high motivational level and an acceptable standard deviation of 0.833, respectively. This result signifies that 76.38% of

the respondents agreed with the statements, whereas 23.62 % responded differently (See Table 6.2 above).

iii) Information Accuracy

The effect of information accuracy on CIE was measured with five-worded statements in which a five-point Likert scale was employed. The mean values of the items ranged from 3.406 to 3.707, above the mid-point of 3.000 out of 5.000. This result indicates an average to high motivational levels. The standard deviation ranged from 0.855 to 0.981, thus attesting that data was very close in value to the mean.

The overall information accuracy mean was 3.617, demonstrating a high motivational level and an acceptable standard deviation of 0.909. This result indicates that 72.34% of the respondents fairly agreed with the statements, whilst 27.66 responded in a different way (See Table 6.2 above).

iv) Information Usefulness

The influence of the usefulness of information on CIE was measured with a five-point Likert scale rating where respondents indicated their perceptions regarding the five-worded statements. The mean values of the items ranged from 3.489 to 3.812, above the mid-point of 3.000 out of 5.000. This result demonstrates a high motivational level.

The acceptable standard deviation ranged from 0.777 to 1.011, thus authenticating that data was very close in value to the mean. The information usefulness overall mean was 3.681, thus indicating a high motivational level and an acceptable standard deviation of 0.898, respectively. This result suggests that 73.62% of the respondents somewhat agreed with the statements, while 26.38% differed in response to this statement in a different way (See Table 6.2 above).

6.2.3.4 Employee Role Clarity

The questionnaire contained five attitude-measuring questions measured with a five-point Likert scale rating. Respondents reflected their opinions about how they perceived employee role clarity in support of CIE. The items' mean values ranged from 3.185 to

3.746, above the mid-point of 3.000 out of 5.000. This result indicates average to high motivational levels.

The acceptable standard deviation ranged from 0.911 to 1.121, thus suggesting that data is very close in value to the mean. The overall mean for employee role clarity of 3.401 indicates an average motivational level and an acceptable standard deviation of 1.025, respectively. This result signifies that 68.02% of the respondents agreed to some extent with the statements, while 31.98% responded differently (See Table 6.2 above).

6.2.3.5 Customer Satisfaction

The five-worded questionnaires were designed to assess respondents' perceptions of customer satisfaction. A five-point Likert scale was used to rate the questionnaire item. The items' mean values ranged from 3.685 to 3.848 above the mid-point of 3.000 out of 5.000. This result demonstrates a high motivational level.

The acceptable standard deviation ranged from 0.791 to 0.889, illustrating that data was very close in value to the mean. The overall customer satisfaction mean was 3.764, indicating a high motivational level and an acceptable standard deviation of 0.836. This result validates that 75.28% of the respondents agreed with the statements, whereas 24.72 % responded differently (See Table 6.2 above).

6.2.3.6 Organisational Performance

The questionnaire was designed to measure how respondents perceived organisational performance, and a five-point Likert scale was applied to answer five-worded statements.

The mean values of the items ranged from 3.236 to 3.721, above the mid-point of 3.000 out of 5.000. This result illustrates an average to high motivational level. The acceptable standard deviation ranged from 0.830 to 0.998, verifying that the data was very close in value to the mean. The overall organisational performance mean was 3.552, indicating a high motivational level and acceptable standard deviation values for information quality and 0.894, respectively. This result suggests that 71.04% of the respondents discreetly

agreed with the statements, whereas 28.96% responded differently (See Table 6.2 above).

6.2.3.7 Competitive Intelligence Embeddedness

The respondents' thoughts on the impact of CIE on customer satisfaction and organisational performance were measured using a five-point scale rating. The mean values for CIE ranged from 3.804 to 4.029, above the mid-point of 3.000 out of 5.000.

This result indicates a high motivational level. At the same time, the acceptable standard deviations ranged from 0.786 to 0.847, indicating that the data was very close in value to the mean. The overall CIE mean was 3.912, indicating a high motivational level and an acceptable standard deviation of 0.818. This result signifies that 78.30% of the respondents discreetly agreed with the statements, whereas 21.70% responded differently (See Table 6.2 above).

6.2.4 Reliability of the Research Instrument

According to Hair et al. (2014a), Cronbach's alpha values range between 0.000 and 1.000; while 1.000 indicates perfect reliability, the value 0.700 is also deemed as the lower level of acceptability. This research employed SPSS version 24.0 to assess the reliability of the questionnaire items.

The reliability statistic for each identified factor is presented in Table 6.2 above. The Cronbach's alpha values for the identified factors range from 0.827 to 0.923, above the lower acceptability limit of 0.700. The findings show that the questionnaire employed in this study is highly reliable.

6.2.5 Measurement of Data Normality

Normality tests for this study was carried out through statistical software. This research employed PLS-SEM; as such, a lack of normality in a variable distribution is likely to distort the results of multivariate analysis. Even with PLS-SEM accuracy, it was imperative to investigate results carefully to ensure that data distribution does not deviate substantially from normal point PLS-SEM analysis (Hair Jr et al., 2017a; Hair et al., 2014a).

Normality evaluation in this study entailed statistically converting and correcting non-normally distributed data in order to remove erroneous goodness of fit (Garson, 2012; Koubaa, Tabbane & Jallouli, 2014).

Meanwhile, in addressing issues of normality, two measures of distribution, namely skewness and kurtosis, were employed in this research (Hair et al., 2014a). To ensure that data was normally dispersed, skewness and kurtosis values were within the ranges of +2.00 to -2.00 (Field, 2013; Garson, 2012; Salelaw & Singh, 2015).

Table 6.3: Assessment of Normality

Variables	Number of Observations	Standard Deviation	Excess Kurtosis	Skewness
CI1	276	0,616	0,706	-0,095
CI2	276	0,633	0,857	-0,423
CI3	276	0,659	0,524	-0,245
CI4	276	0,652	0,639	-0,185
CI5	276	0,596	1,283	-0,247
CS1	276	0,743	1,076	-0,732
CS2	276	0,656	0,373	-0,485
CS3	276	0,710	0,325	-0,539
CS4	276	0,606	0,764	-0,519
CS5	276	0,628	0,742	-0,504
OP1	276	0,630	0,385	-0,410
OP2	276	0,752	-0,100	-0,210
OP3	276	0,699	0,818	-0,314
OP4	276	0,620	1,371	-0,883
OP5	276	0,585	0,601	-0,530

With absolute values for skewness and kurtosis more significant than 2.000 and indicating non-normal data, this study's skewness and kurtosis values ranged from -0.100 to 0.857 and -0.095 to -0.883, indicative that the data was normally distributed for further analysis (See Table 6.3 above).

6.3 Inferential Statistics

Inferential statistics were used to test this study's seventeen hypotheses and to draw conclusions about the relationships between the variables (Gupta, 2012). The following section presents the results of the inferential statistics obtained from this study's research model. The results of the hypothesis tests, the measurement and structural models are presented.

6.3.1 Measurement Model

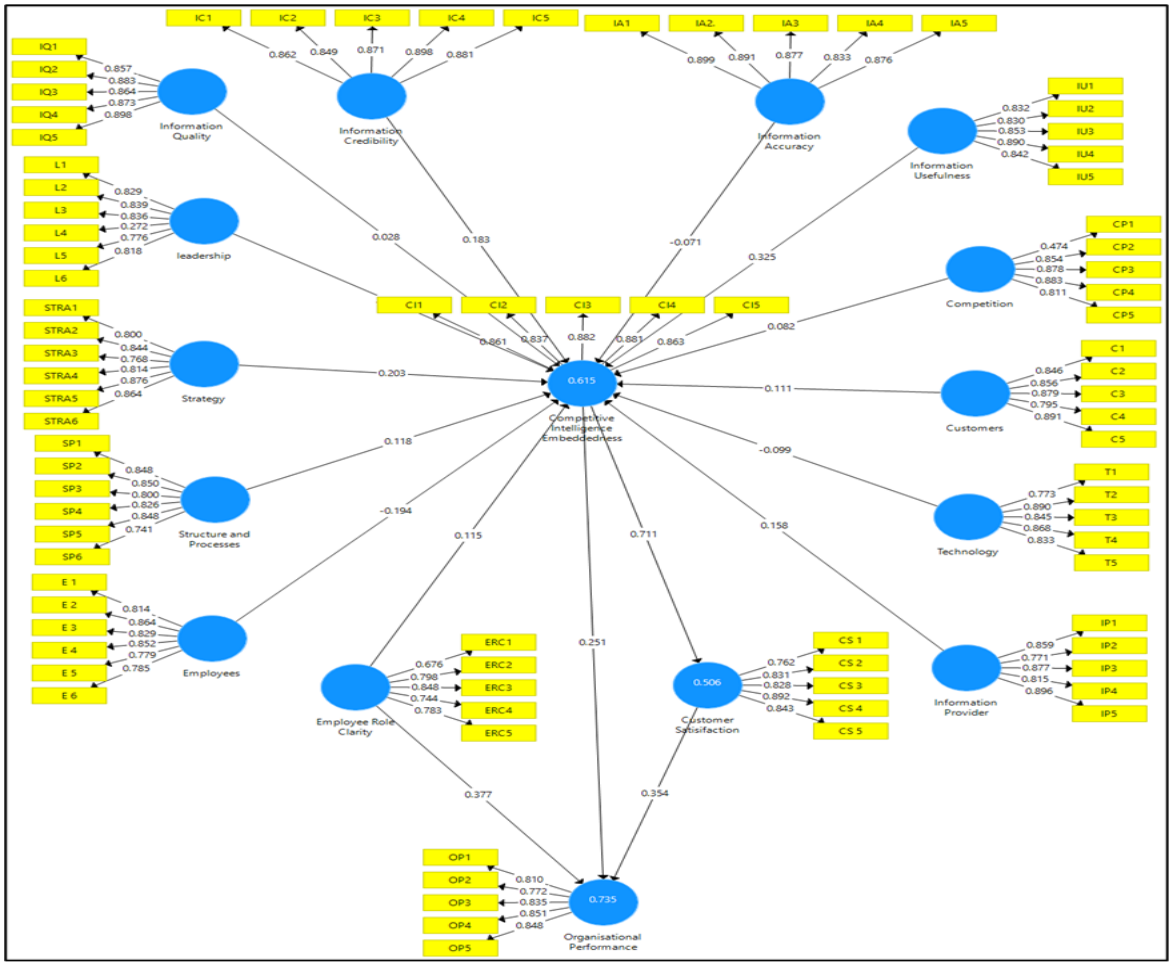
As mentioned above, SmartPLS 3.2.7 was utilised to perform data analysis and appraise this study's measurement model. Figure 6.1 below shows the PLS-SEM output results for this study. Furthermore, it represents the measurement model with correlated values between observed and latent variables of this study.

Figure 6.1 below displays R^2 represented by the numbers in the blue circle showing how much the other latent variables explain the latent variable variance. In comparison, the arrows' numbers represent path coefficients and explain how strong the effect of one variable is on another variable.

Path coefficients were weighted to rank their relative statistical importance in this research. The measurement model is the first step in PLS analysis used to determine the appropriateness of the theoretically defined constructs (Ghulami, Ab Hamid & Zakaria, 2014, p.6).

Furthermore, the measurement model was analysed to verify that the survey questionnaire accurately defines the variables to be tested while ensuring the instrument's reliability (Ghulami et al., 2014, p.6). The following subsections present the results reliability, internal consistency, and validity of this study's observed and unobserved variables.

Figure 6.1: PLS-SEM Measurement Model Output Results



Source: Authors' own compilation

6.3.1.1 Indicator Loadings

Hair et al. (2012a) point out that observed variables with an outer load of 0.700 or greater are considered highly acceptable, whilst the outer loading with a value less than 0.700 should be discarded (Chin, 1998). For this study, the cut-off value accepted for the outer loadings was 0.700; values of 0.272, 0.474 and 0.676, as shown in Table 6.4 below, were discarded. After abandoning the loadings less than the acceptable benchmark of 0.700, the outer loads ranged from 0.741 to 0.899 (see Table 6.4 below). This result shows that more than 50% of the variance of the indicator explains the structure endorsing acceptable item reliability.

6.3.1.2 Internal Consistency and Reliability

Internal consistency was assessed using Cronbach's alpha and CR in the construct dependability, whereas composite reliability was evaluated using rhô-alpha. The cut-off value for internal consistency measured by alpha is 0.700 (Cronbach, 1951).

The cut-off value for composite reliability is the same as any measure of reliability, whereas scores between 0 .600 and 0.700 are considered a good indicator of construct reliability (Henseler & Sarstedt, 2013).

While reliability values as low as 0.700 indicate good reliability in the early stages of research, the results in Table 6.4 demonstrates that all the construct's reliability was higher than 0.800, pointing that higher values of 0.800 or 0.900 should be used in a more advanced study (Nunnally, 1978a).

Cronbach's alpha values ranged from 0.829 to 0.924, and CR values ranged from 0.880 to 0.943; this indicates that the instrument had good internal consistency as all latent construct values exceeded the minimum threshold. The rhô-alpha for all individual constructs ranged from 0.838 to 0.943, indicating high reliability (See Table 6.4 below).

Additionally, values of 0.950 and greater decrease construct validity denote that items are redundant. This research had no redundancy (Diamantopoulos & Durner, 2012; Drolet & Morrison, 2001).

Table 6.4: Summary of the Reflective Outer Model Result

Main Constructs	Indicators	Obs	Indicator Loadings	Cronbach's α	rho_A	CR	AVE
Organisational Factors							
Leadership	L1	276	0,829	0,829	0,877	0,881	0,572
	L2	276	0,839				
	L3	276	0,836				
	L4	276	0,272				
	L5	276	0,776				
	L6	276	0,818				
Strategy	STRA1	276	0,800	0,908	0,914	0,929	0,687
	STRA2	276	0,844				
	STRA3	276	0,768				
	STRA4	276	0,814				
	STRA5	276	0,876				
	STRA6	276	0,864				
Structure & Process	SP1	276	0,848	0,902	0,904	0,925	0,672
	SP2	276	0,850				
	SP3	276	0,800				
	SP4	276	0,826				
	SP5	276	0,848				
	SP6	276	0,741				
Employee	E1	276	0,814	0,903	0,908	0,925	0,674
	E2	276	0,864				
	E3	276	0,829				
	E4	276	0,852				
	E5	276	0,779				
	E6	276	0,785				
Market Factors							
Competition	CP1	276	0,474	0,842	0,868	0,892	0,633
	CP2	276	0,854				
	CP3	276	0,878				
	CP4	276	0,883				
	CP5	276	0,811				
Customer	C1	276	0,846	0,907	0,916	0,931	0,730
	C2	276	0,856				
	C3	276	0,879				
	C4	276	0,795				
	C5	276	0,891				
Technology	T1	276	0,773	0,898	0,912	0,924	0,710
	T2	276	0,890				
	T3	276	0,845				
	T4	276	0,868				
	T5	276	0,833				
Information Providers	IP1	276	0,859	0,900	0,914	0,926	0,714
	IP2	276	0,771				
	IP3	276	0,877				
	IP4	276	0,815				
	IP5	276	0,896				
Information Attributes							
Information Quality	IQ1	276	0,857	0,924	0,926	0,942	0,766
	IQ2	276	0,883				
	IQ3	276	0,864				
	IQ4	276	0,873				
	IQ5	276	0,898				
Information Credibility	IC1	276	0,862	0,921	0,923	0,941	0,761
	IC2	276	0,849				
	IC3	276	0,871				
	IC4	276	0,898				
	IC5	276	0,881				
Information Accuracy	IA1	276	0,899	0,924	0,925	0,943	0,767
	IA2	276	0,891				
	IA3	276	0,877				
	IA4	276	0,833				
	IA5	276	0,876				
Information Usefulness	IU1	276	0,832	0,904	0,906	0,928	0,722
	IU2	276	0,830				
	IU3	276	0,853				
	IU4	276	0,890				
	IU5	276	0,842				
Employee Role Clarity							
Employee Role Clarity	ERC1	276	0,676	0,829	0,838	0,880	0,596
	ERC2	276	0,798				
	ERC3	276	0,848				
	ERC4	276	0,744				
	ERC5	276	0,783				
Customer Satisfaction							
Customer Satisfaction	CS1	276	0,762	0,888	0,892	0,918	0,693
	CS2	276	0,831				
	CS3	276	0,828				
	CS4	276	0,892				
	CS5	276	0,843				
Organisational Performance							
Organisational Performance	OP1	276	0,810	0,881	0,882	0,913	0,679
	OP2	276	0,772				
	OP3	276	0,835				
	OP4	276	0,851				
	OP5	276	0,848				
Competitive Intelligence Embeddeness							
Competitive Intelligence Embeddeness	CIE1	276	0,861	0,916	0,917	0,937	0,748
	CIE2	276	0,837				
	CIE3	276	0,882				
	CIE4	276	0,881				
	CIE5	276	0,863				

Construct validity is divided into convergent and discriminant validity (Taherdoost, 2016b, p. 31). Convergent and discriminant validity were exploited to assess the validity of this study's constructs.

i) Convergent Validity

As indicated above, this study's measurement model has an acceptable quality in terms of its outer loadings since they are above the standard threshold of above 0.700 (Cohen, 1992). The measurement model's convergent validity of this study was evaluated in terms of its indicator loadings and AVE.

Based on the analysis, Table 6.4 above shows that all items in the measurement model displayed outer loadings greater than the acceptable benchmark of 0.700 (Hair et al., 2012a). In tandem, indicator loadings less than 0.700 were removed (Chin, 1998).

Overall this measurement model's indicator loadings were above the standardised benchmark of 0.708, indicating that more than 50% of latent variables explain a substantial part of each indicator's variance and provide acceptable item reliability (Hair Jr et al., 2017a; Hair et al., 2019b). Additionally to factor loadings, each latent construct's Average Variance Extracted (AVE) was calculated (Fornell & Larcker, 1981).

The AVE should be higher than 0.500 for all constructs to confirm convergent validity (Barclay et al., 1995; Hair et al., 2011). Table 6.3 above shows that all AVE for all constructs values ranged from 0.572 to 0.767, that is, more than 0.500. Therefore, convergent validity was confirmed for this study's model. These results confirmed the measurement model's convergent validity and good internal consistency.

ii) Discriminant Validity

This PLS-SEM research does not rely on consistent factor loadings estimates. The measurement model's discriminant validity was assessed by using the Heterotrait-Monotrait-Ratio of correlation (HTMT) rather than the Fornell-Larker criterion and cross-loadings (Henseler et al., 2015; Franke & Sarstedt, 2019; Voorhees, Brady, Calantone & Ramilez, 2016).

Discriminant validity between constructs is established when constructs are significantly distinct from each other, as indicated by HTMT ratios below 0.900 and even more distinct if HTMT ratios are below 0.850 (Henseler et al., 2015). Table 6.5 below shows this study's HTMT ratio of correlation tests. The results from Table 6.5 below illustrate that HTMT values among the related constructs were within the acceptable criterion of less than 0.900, confirming discriminant validity except for Information Usefulness and Information Accuracy, where the HTMT value of 0.925 indicated conceptual similarity.

With a more conservative HTMT value below 0.850, Organisational Performance and Customer Satisfaction were not more distinct. The same outcome was observed between Organisational Performance and Employee Role Clarity; Information Credibility and Information Accuracy; Information Quality and Information Credibility; Information Usefulness and Information Credibility; Organisation Performance and Information Provider; Technology and Structure and Process.

This result indicates that these constructs are potentially related and may be proxies of each other (See Table 6.5 below). Based on the findings of the above results, the reliability and validity tests are satisfactory. Therefore, this study's measurement model is confirmed to be valid and reliable, and it was acceptable to be used in estimating the structural model parameters. The following section measures the Inner Structural Model outcomes of this study.

Table 6.5: Heterotrait-Monotrait Ratio of Correlations Test

Heterotrait-Monotrait Ratio (HTMT)															
	CP	CIE	C	CS	ERC	E	IA	IC	IP	IQ	IU	L	OP	STRA	SP	T
Competition																
Competitive Intelligence Embeddeness	0,631															
Customer	0,827	0,670														
Customer Satisfaction	0,689	0,784	0,770													
Employee Role Clarity	0,676	0,654	0,713	0,729												
Employees	0,765	0,463	0,738	0,632	0,765											
Information Acuracy	0,618	0,702	0,700	0,719	0,664	0,547										
Information Credibility	0,659	0,736	0,746	0,709	0,672	0,563	0,899									
Information Provider	0,727	0,687	0,768	0,831	0,829	0,691	0,744	0,700								
Information Quality	0,669	0,708	0,758	0,697	0,701	0,624	0,826	0,894	0,721							
Information Usefulness	0,648	0,770	0,698	0,765	0,723	0,547	0,925	0,855	0,751	0,826						
Leadership	0,808	0,543	0,735	0,687	0,637	0,741	0,584	0,620	0,680	0,555	0,573					
Organisation Perfomance	0,765	0,794	0,761	0,868	0,870	0,664	0,780	0,771	0,883	0,772	0,836	0,736				
Strategy	0,680	0,621	0,654	0,640	0,569	0,590	0,595	0,624	0,572	0,637	0,583	0,769	0,662			
Structure and Processes	0,835	0,546	0,705	0,618	0,656	0,842	0,618	0,582	0,714	0,644	0,594	0,793	0,722	0,644		
Technology	0,741	0,491	0,627	0,527	0,652	0,738	0,640	0,571	0,640	0,645	0,632	0,635	0,681	0,598	0,856	

6.3.2 Structural Model (Inner Model)

The structural model in this study was reviewed as advised by Ringle et al. (2020) after the measurement model was successfully validated, and consistent with the evaluation guidelines proposed by Hair et al. (2019b), Yahaya et al. (2019), and Benitez et al. (2020) were considered in evaluating this study's structural model.

The model's overall Goodness-of-Fit (GOF) was used as the starting point of the model assessment (Henseler et al., 2016, p. 9). This study's structural model employed SmartPLS 3.2.7 and PLS-SEM to perform the explanatory and the model's predictive relevancy (Henseler, 2018). Aside from assessing the model's in-sample and out-of-sample predictive abilities, the researcher also explored the collinearity among the exogenous constructs and tested the significance of path coefficients and indirect effects.

6.3.2.1 Model Fit

This subsection presents the outcome of the Goodness of Fit (GOF) index from Tenenhaus et al. (2005) that was used to validate that the structural model satisfactorily explains the empirical data. Additionally, the results of the overall fit of the estimated model obtained from the SRMR and the RMS_theta are presented (Benitez et al.,2020; Hair Jr et al., 2017; Henseler et al.,2014; Yahaya et al., 2019).

i) Goodness-of-Fit Index

The GOF is the square root of the product between the average communality index and the average R^2 for the model (Tenenhaus et al., 2005, p.173). According to Wetzels, Odekerken-Schröder and Van Oppen (2009), the AVE for each latent variable equals the corresponding communality index. The GOF values lie between 0 and 1, where values of 0.100 (small), 0.250 (medium), and 0.360 (large) indicate the global validation of the path model (Wetzels et al., 2009).

A good model fit shows that a model is parsimonious and plausible (Henseler et al., 2016). As Wetzels et al. (2009) recommended, the GOF index for this research was calculated using this formula: $\sqrt{}$ (Average R^2 x Average AVE), as shown in Table 6.6.

The GOF index for this study's model was measured as 0.656 and 0.652, respectively, for both the R^2 and the adjusted R^2. The index shows that empirical data fits the model satisfactory and has substantial predictive power compared to baseline values (See Table 6.6 below).

While the results presented in Table 6.6 below indicated a good fit with the model, the usefulness of the GOF both conceptually and empirically was criticised and found to be an effective measure for PLS-SEM (Henseler & Sarstedt, 2013; Henseler et al., 2014). This study measured the overall fit of the estimated model was also measured in this study.

Table 6.6: Goodness-of-Fit Index Calculation

Constructs	AVE	R^2	R^2 Adjusted
Competition	0,633		
Customer	0,730		
Information Provider	0,714		
Technology	0,710		
Leadership	0,572		
Strategy	0,687		
Structure and Processes	0,672		
Employees	0,674		
Information Acuracy	0,767		
Information Credibility	0,761		
Information Quality	0,766		
Information Usefulness	0,722		
Competitive Intelligence Embeddeness	0,748	0,615	0,596
Customer Satisfaction	0,693	0,506	0,504
Employee Role Clarity	0,596		
Organisation Perfomance	0,679	0,735	0,732
Average Values	0,695	0,619	0,611
AVE x R^2		0,430	0,425
GOF =$\sqrt{}$ AVE x R^2		**0,656**	**0,652**

ii) Overall fit of the Estimated Model

The global model fit can be assessed through a bootstrap-based test for overall model fit or by measures of overall model fit, such as the SRMR (Dijkstra & Henseler, 2015; Henseler et al.,2014; Henseler et al., 2016). The SRMR, a measure of estimated model fit with the RMS_theta, the root mean squared residual covariance matrix of the outer model residuals used to evaluate this reflectively measured construct model.

Hu and Bentler (1998) have suggested that SRMR thresholds of less than or equal to 0.080 indicate a good model fit, with a lower SRMR being a better fit. In contrast, SRMR values less than 0.100 or 0.080 in more conservative and normal models are considered a good fit (Hu & Bentler, 1999; Henseler et al., 2014). The results in Table 6.7 below illustrate that the SRMR were 0.055 and 0.078 for the estimated and saturated models, respectively, thus indicating an acceptable and good model fit for this study (Hu & Bentler, 1999).

Table 6.7: Model Fit Summary and RMS_theta

Model Fit Summary		
	Saturated Model	Estimated Model
SRMR	0,055	0,078
d_ULS	10,739	21,704
d_G	4,876	5,077
Chi-Square	6765,515	6915,411
NFI	0,715	0,709

Rms_Theta	
RMS_ Theta	0,101

The Chi-Square and the NFI were also measured to evaluate the overall model fit. This research did not exclusively rely on them due to their limitations (Kline, 2005a; Hooper et al., 2008). Additionally, the Chi-square-based model fit measures and their extensions applicable in CB-SEM are not suitable for PLS-SEM (Hair et al., 2019b, p. 7).

RMS_theta, the root mean squared residual covariance matrix of the outer model residuals, was therefore considered a fitness measure for the structural model (Lohmöller, 1989). The RMS_theta was measured since SRMR thresholds are not readily transferable to RMS_theta (Hair et al., 2014b). Table 6.7 illustrates that the RMS_theta value was 0.101, indicating a well-fitting model since it is below the benchmark of 0.120 (Hair et al., 2014b). Furthermore, the SRMR and RMS_theta results provide evidence of handling model misspecifications (Hair et al., 2014b).

While there are no golden rules for assessing model fit, reporting a variety of indices was necessary because different indices reflect various aspects of model fit (Crowley & Fan, 1997). This research further investigated all discrepancies of d_ULS and d_G below the 95 per cent quantile of the bootstrap discrepancies (HI95) to quantify a very good measurement model fit (Hair et al., 2014b). Table 6.8 below presents the results of the bootstrap-based test for the overall model fit.

Table 6.8: Bootstrap-based test for Overall Model Fit

Exact Fit Bootstrap discrepancies (HI95)					
Descrepancy	Saturated Model	HI95	Estimated Model	HI95	Conclusion
d_ULS	4,975	6,151	5,999	4,826	Supported
d_G	4,037	7,632	4,060	4,862	Supported
SRMR	0,037	0,042	0,041	0,046	Supported

All discrepancy measures were below the 95 percent quantile of their reference distribution, as shown in Table 6.8. (HI95). However, the overall model fit thresholds in the PLS-PM context should be carefully considered. Therefore, preliminary and future methodological studies will need to investigate them more (Benitez et al., 2020, p.8).

Because information and expertise are scarce about precise fit measures, their use, behaviour, significance, and suitable application have yet to be documented in PLS-SEM literature. This study attained SRMR values of 0.055 and 0.078 for the estimated and

saturated models. The RMS_theta value of 0.101 quantify this study's good and well-fitting model.

6.3.2.2 Collinearity Assessment

According to Hair et al. (2019b), evaluating a sequence of regression equations to identify the links between the constructs yields structural model coefficients; they are more prone to creating common variations which are susceptible to increasing the levels of collinearity among the latent variables (Kock, 2015). This study examined collinearity before assessing the structural model to ensure that regression results are free from common method bias (Hair et al., 2019b; Kock, 2015).

According to Becker, Ringle, Sarstedt and Völckner (2015), and Mason and Perreault Jr (1991), the Variance Inflation Factor (VIF) values above 5.00 are indicative of plausible collinearity issues among the predictor constructs. Collinearity matters can also occur at VIF values of 3.000-5.000.

Since each indicator's variance inflation factor (VIF) value should be less than 5.000, the VIF value of the cut-off value of 5 was used to assess collinearity in this research (Mooi, Sarstedt & Mooi-Reci, 2017; Hair et al., 2011). For this research, vertical and lateral collinearity was conducted among the latent variables of this study to address model contamination (Kock & Lynn, 2012). Both the inner and outer VIF values were then evaluated. Table 6.9 and Table 6.10 below provide a summary of the collinearity assessment results.

Table 6.9 also presents the results of the initial examination of the outer VIF values ranging between 2.003 to 3.103 for all variables, including control variables which are lower than the threshold of 5.000, thus confirming that the research model is free from common method bias (Cenfetelli & Bassellier, 2009; Kock & Lynn, 2012; Petter et al., 2007).

Table 6.9: Collinearity Statistics (Outer VIF Values)

Outer VIF Values	
Variable	VIF
Organisational Factors	
Leadership	2,003
Strategy	2,639
Structure and Process	2,356
Employees	2,503
Market Factors	
Customer	2,800
Competition	2,523
Information Providers	2,493
Technology	2,480
Information Attributes	
Information Accuracy	3,038
Information Credibility	3,103
Information Quality	3,079
Information Usefulness	2,433
Emplyee Role Clarity	
Employee Role Clarity	1,777
Customer Satisfaction	
Customer Satisfaction	2,364
Competitive Intelligence Embeddedness	
Competitive Intelligence Embeddedness	2,752
Organisational Performance	
Organisational Performance	2,270
Overall Collinearity	2,538

Notably, the Inner VIF values show that most of the VIF values were below the threshold of 5.000, apart from only two variables showing 5.135 and 5.013 for IA→CIE and IC→CIE, respectively (See Table 6.10 below).

Table 6.10: Collinearity Statistics (Outer VIF Values)

Inner VIF Values	
Variable	VIF
Organisational Factors	
Leadership→CIE	2,924
Strategy→CIE	2,222
Structure and Process→CIE	4,251
Employees→CIE	3,240
Market Factors	
Competition→CIE	3,264
Customers→CIE	3,314
Information Providers→CIE	3,131
Technology→CIE	2,902
Information Attributes	
Information Accuracy→CIE	5,135
Information Credibility→CIE	5,013
Information Quality→CIE	4,328
Information Usefulness→CIE	4,311
Employee Role Clarity	
Employee Role Clarity→CIE	2,712
Employee Role Clarity→OP	1,761
Customer Satisfaction	
Customer Satisfaction→OP	2,384
Competitive Intelligence Embeddeness	
Competitive Intelligence Embeddeness→CS	1,000
Competitive Intelligence Embeddeness→OP	2,136

VIF values greater than 5.000 indicate a cause for concern regarding multicollinearity. Similarly, VIF values of 10 or greater indicate severe multicollinearity (Gareth, Daniela, Trevor & Robert, 2013; Mooi et al., 2017). This research's mediating and moderating variables of interest, CIE→CS, CIE→OP, and CS→OP, have VIF values less than the conservative threshold of 3.300 (Diamantopoulos & Siguaw, 2006).

While there is some correlation between this model's regression variables, these results indicate that multicollinearity is not a severe problem in the structural model; hence the model's explanatory power was evaluated in the following section.

6.3.2.3 The Explanatory Power of the Model

The coefficient of determination (R^2) measures the structural model's predictive accuracy and reflects the total effect size and variation explained in the endogenous construct (Hussain et al., 2018, p.12). The R^2 measures the model's explanatory power (Shmueli & Koppius, 2011). R^2 values range from 0.000 to 1.00, with higher values indicating higher predictive accuracy and explanatory power (Hair Jr et al., 2017a; Hair et al., 2019b).

According to Hair et al. (2013), and Henseler et al. (2009), an R^2 value of 0.750, 0.500 and 0.260 are considered substantial, moderate, and weak, respectively. The results of the R^2 values for the endogenous latent constructs are presented in Table 6.11 below.

Table 6.11: Coefficient of determination (R^2)

R Square		
Construct	R^2	R^2 Adjusted
Competitive Intelligence Embeddeness	0,615	0,596
Customer Satisfaction	0,506	0,504
Organisation Perfomance	0,735	0,732

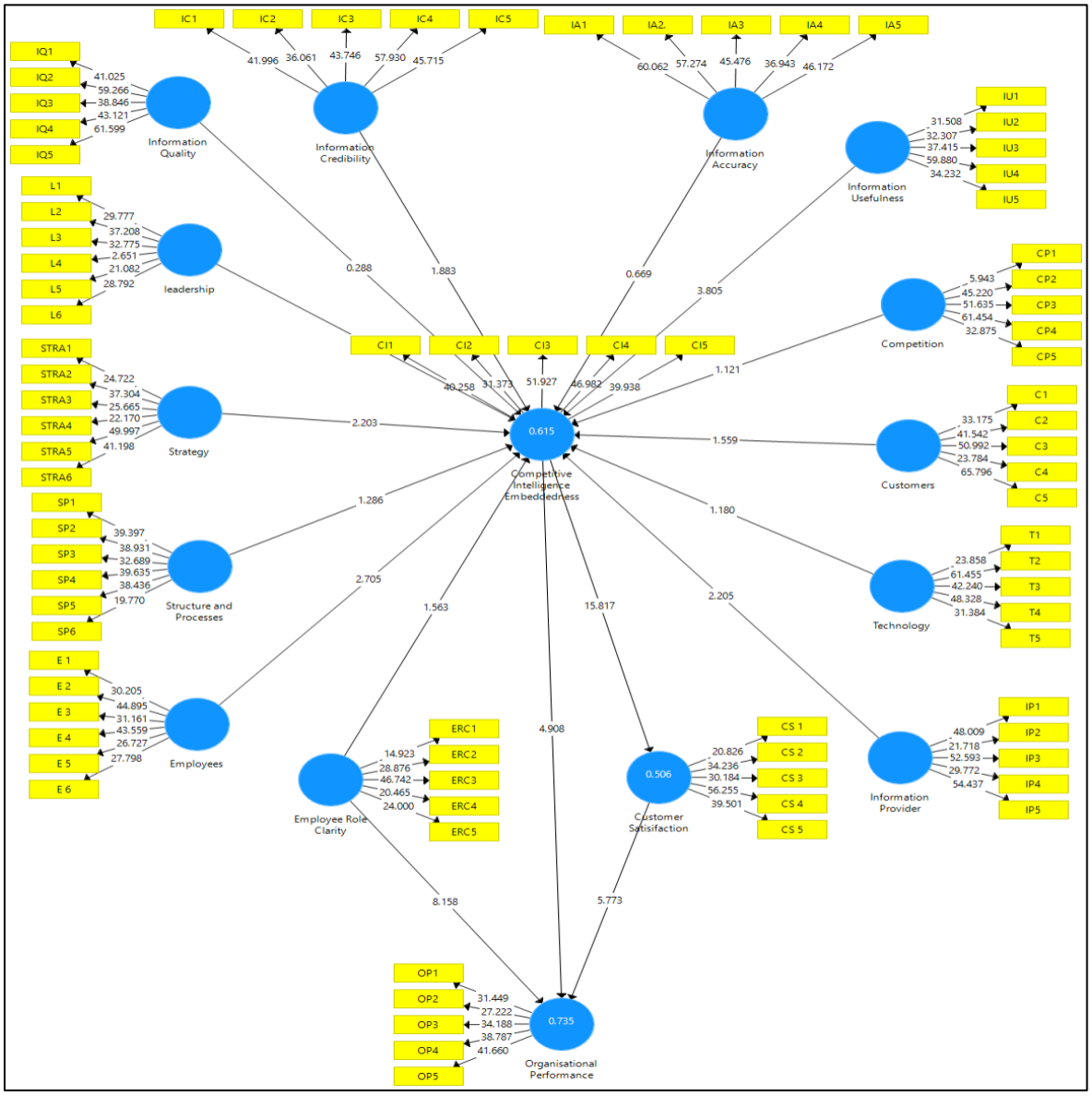
Table 6.11 demonstrates that the R^2 values were 0.615, 0.506 and 0.735 for CIE, CS, and OP, respectively, and they are collectively considered moderately strong. In tandem, this study's adjusted R^2 values of 0.596, 0.504 and 0.732 for CIE, CS, and OP, respectively, and after taking into account model complexity and sample size, it was helpful to compare different models or the explanatory power of a model across different data sets (Henseler et al., 2016, p.11).

The modified R^2 improved the precision and dependability of this study by considering the influence of extra independent factors that might distort the findings of R^2 measurements.

Figure 6.2 below represents this study's structural and inner path models for the endogenous latent constructs. This study's inner path models were 0.615, 0.506, and 0.735 for the CIE, CS, and OP endogenous latent constructs.

This result shows that 61.5% of the change in CIE was due to thirteen latent constructs in the model, while 50.60% of the variation in CS was ascribed to the mediating construct CIE. Additionally, the variance of 73.50% in OP was the consequence of the mediating (CIE), moderating (CS), and the exogenous variable (ERC).

Figure 6.2: Structural Model



Source: Author's own compilation

6.3.2.4 Predictive Relevancy of the Model

The Q^2 value is a metric used to evaluate the path model's predictive accuracy (Geisser, 1974; Stone, 1974). This study used Stone-Geisser's predictive relevance (Q^2) to ensure that data points of indicators in the reflective measurement model of the endogenous construct were predicted accurately (Wong, 2016).

The Q^2 was calculated to measure this research's predictive communality or redundancy (Shmueli et al., 2016, p.4557). This research evaluated the model's predictive performance using a combination of the in-sample and out of sample and predictions on entirely new data (Shmueli et al., 2016). The predictive relevancy was in two stages: blindfolding and cross-validation, alongside a PLSpredict-based assessment. Therefore, blindfolding procedures and cross-validation redundancy with a holdout sample were used to calculate the Q^2 (Geisser, 1974; Stone, 1974; Tenenhaus et al., 2005).

Hair et al. (2019b, p.12) suggested rules of thumb for Q^2 values higher than 0.000, 0.250 and 0.500 to depict the PLS-path model's small, medium, and large predictive relevance. Q^2 values larger than 0.000 thus indicate that the model has predictive relevance for a specific reflective endogenous latent variable. In contrast, the values of 0.000 and below indicate a lack of predictive relevance (Hair Jr et al., 2017a). Table 6.12 hereunder summarises blindfolding and cross-validated Q^2 statics results for this study.

Notably, the blindfolding and cross-validated redundancy measures showed Q^2 values of 0.441, 0.343 and 0.443 for CIE, CS, and OP, respectively, which were greater than 0.000, indicative of the exogenous constructs having a good predictive relevance for the endogenous constructs under consideration Hair Jr et al. (2017a).

Table 6.12: Results of the Predictive Relevance (Q^2)

Blindfolding and Construct Crossvalidated Redundancy			
Construct	SSO	SSE	Q^2 (=1-SSE/SSO)
Competitive Intelligence Embeddeness	1380,000	771,159	0,441
Customer Satisifaction	1380,000	906,973	0,343
Organisational Performance	1380,000	699,132	0,493

Because the Q^2 is known for displaying a strong impression of redundancy within a dataset, employing highly correlated data from related items of the same construct and case as the items predicted has many drawbacks (Shmueli et al., 2016, p.4557).

Meanwhile, PLSpredict, a holdout sample-based procedure that generates case-level predictions on an item or a construct level, was used to overcome these limitations (Shmueli et al., 2019; Shmueli et al., 2016). The prediction errors for all endogenous construct indicators were also examined using PLSpredict instead of the model's critical endogenous construct (Hair et al., 2019b).

Consequently, Shmueli et al. (2019) assert that a positive Q^2 prediction indicates that the model possesses the predictive ability, whereas the opposite is true with a negative Q^2_predict predict value.

As recommended by Shmueli et al. (2016), the Mean Absolute Error (MAE), which measures the average magnitude of the errors, and the Root Mean Squared Error (RMSE) were drawn to quantify the amount of prediction error. Importantly, this research compared the RMSE and MAE values with a naïve benchmark (Hair et al., 2019b).

Table 6.13 presents CIE, CS, and OP results since they are critical endogenous constructs within the structural model. The review of the Q^2_predict values in the PLS-SEM results ranged from 0.306 to 0.506. All the Q^2_predict values were positive, indicating the model's predictive accuracy (See Table 6.13).

Table 6.13: PLSpredict Results Based on Assessing MAE and RMSE Values

PLS Results				LM Results		Prediction Error	
Constructs	RMSE	MAE	Q^2_predict	RMSE	MAE	PLS RMSE-LMRMSE	PLS MAE-LM MAE
CIE1	0,616	0,476	0,387	0,664	0,499	-0,048	-0,022
CIE2	0,633	0,479	0,393	0,754	0,548	-0,121	-0,069
CIE3	0,659	0,505	0,397	0,785	0,608	-0,126	-0,103
CIE4	0,652	0,495	0,371	0,764	0,581	-0,112	-0,086
CIE5	0,596	0,449	0,483	0,713	0,518	-0,117	-0,069
CS 1	0,743	0,569	0,306	0,855	0,644	-0,112	-0,075
CS 2	0,656	0,506	0,354	0,797	0,593	-0,141	-0,086
CS 3	0,710	0,553	0,359	0,859	0,658	-0,149	-0,106
CS 4	0,606	0,454	0,427	0,644	0,493	-0,038	-0,039
CS 5	0,628	0,487	0,372	0,707	0,539	-0,079	-0,052
OP1	0,630	0,498	0,463	0,730	0,556	-0,100	-0,058
OP2	0,752	0,604	0,435	0,777	0,579	-0,025	0,024
OP3	0,699	0,550	0,457	0,826	0,632	-0,127	-0,083
OP4	0,620	0,478	0,455	0,746	0,567	-0,126	-0,088
OP5	0,585	0,457	0,506	0,677	0,504	-0,093	-0,047

Additionally, RMSE values revealed that none of the items in the PLS-SEM analysis had higher RMSE values than the naïve LM benchmark, indicating that a model has a high level of predictive power (See Table 6.13 above). However, when comparing MAE values with the naïve LM benchmark, the PLS-SEM analysis showed that one item, OP2 yielded moderate prediction errors suggesting a medium predictive power (Hair et al., 2019b).

Overall, the structural model has met all the model's predictive accuracy requirements showing a medium to a large predictive effect. According to Hair et al. (2019b), once the model's explanatory and predictive power are validated. The path coefficients should be tested for their statical significance and relevance. For that reason, the following section presents the results of this study's path coefficients.

6.3.2.5 Path Coefficients Analysis

According to Yahaya et al. (2019,p.11), a path is statistically significant if it is different from 0.000 at a 5% significance level when its p-value is below 0.050 or when the 95% bootstrap percentile confidence interval constructed around the estimate does not cover the zero. The significance of the route coefficients and their values were evaluated using bootstrapping in this study, which typically falls between -1.000 and +1.000 (Hair et al., 2019b, p. 13).

Therefore, path coefficients close to +1.000 indicate a robust positive relationship, while path coefficients close to -1.000 indicate a strong negative relationship. The closer the estimated coefficients are to 0.000, the weaker the relationships (Hair Jr et al., 2017a).

This research, therefore, considered values close to 0.000 as statistically insignificant. A bootstrapping procedure of 5000 sub-samples with no sign changes was carried out to test the significance of the path coefficient and the corresponding T-statistics values (Hussain et al., 2018; Yahaya et al., 2019).

Additionally, 5000 bootstrapping sub-samples were used to create p-values with the Bias-Corrected Percentile Bootstrap (BCa) confidence intervals (Aquirre-Urreta & Rönkkö, 2018). Critical T-values of 1.960 for a two-tailed test with the corresponding p-value less than 0.050 at a 5% significance level were used in this study (Hair Jr et al., 2017a).

Table 6.14 below presents the significance of path coefficients and T-statistics values after bootstrapping procedures were carried out with no sign changes (Streukens & Leroi-Werelds, 2016).

With the p-value only reporting the existence of the effect, this research reports on the substantive significance of effect size (f^2) and statistical significance of the p-values (Sullivan & Feinn, 2012, p. 279). Meanwhile, f^2 was assessed to quantify the significant effects of the p-values (Henseler et al., 2016).

The f^2 values of 0.020, 0.150, and 0.350 represent small, medium, and large effects (Benitez et al., 2020; Cohen, 1988; Hair Jr et al., 2017a). This research employs the p-values, T-values and f^2 to report on the statistical significance of the path coefficients (See Table 6.14 below). The following subsection presents the significance of this model's path coefficients.

Table 6.14: Path Coefficients

Variables	Standerdized Beta	STDEV	T-Value	p-Values	Effect size (f^2)
Organisational Factors					
Strategy→Competitive Intelligence Embeddeness	0,203	0,091	2,231	0,026	0,048
Leadership→Competitive Intelligence Embeddeness	-0,081	0,074	1,092	0,275	0,006
Structure and Processes→Competitive Intelligence Embeddeness	0,118	0,092	1,273	0,203	0,008
Employees→Competitive Intelligence Embeddeness	-0,194	0,074	2,631	0,009	0,030
Information Attributes					
Information Quality→Competitive Intelligence Embeddeness	0,028	0,095	0,296	0,767	0,000
Information Credibility→Competitive Intelligence Embeddeness	0,183	0,097	1,899	0,058	0,017
Information Accuracy→Competitive Intelligence Embeddeness	-0,071	0,104	0,688	0,492	0,003
Information Usefulness→Competitive Intelligence Embeddeness	0,325	0,087	3,754	0,000	0,064
Market Factors					
Competition→Competitive Intelligence Embeddeness	0,082	0,073	1,126	0,260	0,005
Customers→Competitive Intelligence Embeddeness	0,111	0,072	1,538	0,124	0,010
Technology→Competitive Intelligence Embeddeness	-0,099	0,085	1,169	0,242	0,009
Information Provider→Competitive Intelligence Embeddeness	0,158	0,073	2,171	0,030	0,021
Employee Role Clarity					
Employee Role Clarity→Competitive Intelligence Embeddeness	0,115	0,073	1,578	0,115	0,013
Employee Role Clarity→Organisational Performance	0,377	0,047	8,094	0,000	0,305
Competitive Intelligence Embeddeness					
Competitive Intelligence Embeddeness→Customer Satisfaction	0,711	0,045	15,953	0,000	1,023
Competitive Intelligence Embeddeness→Organisational Performance	0,251	0,052	4,834	0,000	0,111
Customer Satisfaction					
Customer Satisifaction→Organisational Performance	0,354	0,061	5,792	0,000	0,198

i) Organisational Factors

The organisational factors such as employee capabilities, leadership, strategy, structure, and process influence CIE are represented by the variables in Table 6.14 above. The findings in Table 6.14 and Figure 6.2 indicate that regression paths between strategy and CIE (β = 0.203, T=2.631, p <0.050, f^2= 0.048); employee's capabilities and CIE (β = -0.194, T=1.092, p <0.050, f^2= 0.030) were statistically significance indicating a medium to a large effect (f^2) on CIE.

This result also suggests that an increase in one standard deviation for strategy and employee increases CIE by 0.203 and -0.194 standard deviations if all the other exogenous constructs are kept constant. In contrast, the regression paths between leadership and CIE (β = -0.081, T=1.092, p <0.050, f^2= 0.006); structure and process along with CIE (β = 0.118, T=2.631, p <0.050, f^2= 0.008) were statistically insignificant, thereby indicating a weak effect (f^2) on CIE.

ii) Information Attributes

Information attributes such as information accuracy, credibility, quality, and usefulness that impact CIE are represented by the exogenous constructs in Table 6.14 above. The findings in Table 6.14 and Figure 6.2 indicate that regression paths between information quality and CIE (β = 0.208, T=0.296, p >0.050, f^2= 0.000) information credibility and CIE (β = 0.183, T=1.899, p >0.050, f^2= 0.017) with information accuracy and CIE (β = -0.071, T=0.688, p >0.050, f^2= 0.003) were statistically insignificant, thus indicating a weak effect (f^2) on CIE.

Additionally, when observing the significance of regression paths between information usefulness on CIE, the findings from Table 6.14 and Figure 6.2 show (β = 0.325, T=3.754, p <0.050, f^2= 0.064) endorsing statical significance with a medium effect (f^2) between information usefulness and CIE. This result suggests that increasing one standard deviation for information usefulness increases CIE by 0.325 standard deviations if all the other exogenous constructs are kept constant.

iii) Market Factors

The impact of market factors such as customer insights, competition, technology, and information providers have a bearing on CIE and are shown in Table 6.14. The findings in Table 6.14 and Figure 6.2 illustrate that the regression paths between competition and CIE (β = 0.082, T=1.126, p > 0.050, f^2= 0.005), customers insights and CIE (β = 0.111, T=1.538, p >0.050, f^2= 0.010), as well as technology and CIE (β = -0.099, T=1.169, p >0.050, f^2= 0.009) showed statistically insignificant with a weak effect (f^2) on CIE.

The regression paths between information providers and CIE from Table 6.14 and Figure 6.2 show (β = 0.158, T=2.171, p <0.050, f^2= 0.021) supporting statical significance between information providers and CIE, *albeit,* somewhat with a small effect (f^2) on CIE.

Furthermore, these results demonstrate that an increase in one standard deviation for information providers increases CIE by 0.325 standard deviations if all the other exogenous constructs are kept constant.

iv) Employee Role Clarity

The effect of employee role clarity-related factors on CIE and organisational performance was evaluated. The findings from Table 6.14 and Figure 6.2 validate that the regression path between employee role clarity and CIE (β = 0.115, T=1.578, p > 0.050, f^2= 0.013) was statistically insignificant and attributed to a week effect (f^2) on CIE.

However, when observing the regression path between employee role clarity and organisational performance, the results showed a statistical significance with a moderate to large effect between employee role clarity and organisational performance (β = 0.377, T=8.094, p<0.050, f^2= 0.305). This finding signifies that an increase in one standard deviation in employee role clarity increases organisational performance by 0.377 standard deviations if all the other exogenous constructs are kept constant.

v) Competitive Intelligence Embeddedness

The effect of CIE-related factors on customer satisfaction and organisational performance is shown in Table 6.14 above. The findings from Table 6.14 and Figure 6.2 verify that the regression paths between CIE and customer satisfaction (β = 0.711, T=15.953 p<0.050, f^2= 1.023) together with CIE and organisational performance (β = 0.251, T=4.834, p<0.050, f^2= 0.111) showed a strong statistical significance with a medium to a large effect on organisation performance and customer satisfaction.

These studies suggest that raising the CIE by one standard deviation boosts customer satisfaction and organisational performance by 0.711 and 0.251 standard deviations if all the other exogenous constructs are constant.

vi) Customer Satisfaction

The regression path between customer satisfaction and organisational performance (β = 0.354, T=5.792, p<0.050, f^2= 0.198) was statistically significant with a medium effect. The findings from Table 6.14 and Figure 6.2 also demonstrate that an increase in one standard deviation in customer satisfaction increases organisational performance by 0.354 standard deviations if all the other exogenous constructs are kept constant.

Overall, the cumulative f^2 values of all thirteen exogenous constructs on CIE had a weak effect on the value of the R^2, whereas the f^2 of the mediating, moderating and exogenous constructs on organisational performance had a moderate to large effect on the value of the R^2 (Cohen, 1988). After a successful evaluation of the significance of path coefficients, the following section presents the results of the hypothesis testing.

6.3.2.6 Hypothesis Testing

In the previous section, the β value was verified for its significance level through the T-statistics, the effect size (f^2), and the p-values. Hahn and Ang (2017) stress that p-values do not measure the effect's size or the importance of a result. Likewise, p-values do not provide a good measure of evidence regarding a model or hypothesis.

In testing this study's hypothesis, the β values of every path in the hypothesised model were computed. The significance of the hypothesis was tested through the β value, T-statistics, and the effect size (f^2). The bootstrapping procedure was also employed to assess the hypothesis's relevance (Chin, 1998). Table 6.15 presents the results of this study's hypothesis testing.

As suggested, the p-values, T-values and f^2 were used to test the statistical significance of this study's hypothesis (See Table 6.15 below). The results of the significance of the hypothesis testing are presented in the following subsections.

Table 6.15: Hypothesis Testing

Hypothesis	Hypothesized Path	Standerdized Beta	STDEV	T-Statistics	p-Values	Effect size (f^2)	Decision
Organisational Factors							
H1→CIE	Strategy -> Competitive Intelligence Embeddeness	0,203	0,091	2,231	0,026	0,048	Supported
H2→CIE	Leadership -> Competitive Intelligence Embeddeness	-0,081	0,074	1,092	0,275	0,006	Not Supported
H3→CIE	Structure and Processes -> Competitive Intelligence Embeddeness	0,118	0,092	1,273	0,203	0,008	Not Supported
H4→CIE	Employees -> Competitive Intelligence Embeddeness	-0,194	0,074	2,631	0,009	0,030	Supported
Information Attributes							
H5→CIE	Information Quality -> Competitive Intelligence Embeddeness	0,028	0,095	0,296	0,767	0,000	Not Supported
H6→CIE	Information Credibility -> Competitive Intelligence Embeddedness	0,183	0,097	1,899	0,058	0,017	Not Supported
H7→CIE	Information Accuracy -> Competitive Intelligence Embeddeness	-0,071	0,104	0,688	0,492	0,003	Not Supported
H8→CIE	Information Usefulness -> Competitive Intelligence Embeddeness	0,325	0,087	3,754	0,000	0,064	Supported
Market Factors							
H9→CIE	Competition -> Competitive Intelligence Embeddeness	0,082	0,073	1,126	0,260	0,005	Not Supported
H10→CIE	Customers -> Competitive Intelligence Embeddeness	0,111	0,072	1,538	0,124	0,010	Not Supported
H11→CIE	Technology -> Competitive Intelligence Embeddeness	-0,099	0,085	1,169	0,242	0,009	Not Supported
H12→CIE	Information Provider -> Competitive Intelligence Embeddeness	0,158	0,073	2,171	0,030	0,021	Supported
Employee Role Clarity							
H13→CIE	Employee Role Clarity -> Competitive Intelligence Embeddeness	0,115	0,073	1,578	0,115	0,013	Not Supported
H14→OP	Employee Role Clarity -> Organisational Performance	0,377	0,047	8,094	0,000	0,305	Supported
Competitive Intelligence Embeddeness							
H15→CS	Competitive Intelligence Embeddeness -> Customer Satisifaction	0,711	0,045	15,953	0,000	1,023	Supported
H17→OP	Competitive Intelligence Embeddeness -> Organisational Performance	0,251	0,052	4,834	0,000	0,111	Supported
Customer Satisfaction							
H16→OP	Customer Satisifaction -> Organisational Performance	0,354	0,061	5,792	0,000	0,198	Supported

i) Organisational Factors

The organisational factors such as employees capabilities, leadership, strategy, structure, and process are predicted to influence CIE, represented by the hypothesised path in Table 6.13 above. As predicted, the findings in Table 6.15 and Figure 6.2 indicate H1(β = 0.203, T=2.231, p <0.050, f^2= 0.048) and H4 (β = -0.194, T=2.631, p <0.050, f^2= 0.030) confirming that both employee capabilities and strategy contributed significantly to CIE.

In contrast, the results for H2 (β = -0.081, T=1.092, p >0.050, f^2= 0.006) and H3 (β = 0.118, T=1.273, p <0.050, f^2= 0.008) show insignificance contribution for both leadership structure and process when measured with CIE. The findings have supported H1 and H4, while H2 and H3 were not supported.

ii) Information Attributes

Information attributes such as information accuracy, credibility, quality, and usefulness that influence CIE are predicted in the hypothesised path, as shown in Table 6.13 above. The findings in Table 6.15 and Figure 6.2 illustrate H5 (β = 0.028, T=0.296, p >0.050, f^2= 0.000); H6 (β = 0.183, T=1.899, p >0.050, f^2= 0.017) and H7 (β = -0.071, T=0.688, p >0.050, f^2= 0.003). This result signifies that information accuracy, credibility and quality have no statistical significance to CIE.

Furthermore, when observing the significance of information usefulness on CIE, the findings from Table 6.15 and Figure 6.2 show H8 (β = 0.325, T=3.754, p <0.050, f^2= 0.064) endorsing statical significance between information usefulness and CIE. H8 was robustly supported, while H5, H6 and H7 were not supported.

iii) Market Factors

The impact of market factors such as customer insights, competition, technology, and information providers on CIE are predicted in Table 6.15 above. The findings in Table 6.15 and Figure 6.2 illustrate H9 (β = 0.082, T=1.126, p > 0.050, f^2= 0.005); H10 (β = 0.111, T=1.538, p >0.050, f^2= 0.010) and H11 (β = -0.099, T=1.169, p >0.050, f^2= 0.009).

This result indicates that when the impact of customer insights, competition, and technology was assessed with CIE, no statistical significance was found between these variables and CIE. The findings from Table 6.15 and Figure 6.2 show H12 (β = 0.158, T=2.171, p <0.050, f^2= 0.021) advocating statical significance between information providers and CIE. Therefore, H12 was strongly supported while H9, H10 and H11 were not supported.

iv) Employee Role Clarity

The influence of employee role clarity-related factors on CIE and organisational performance was evaluated. The findings from Table 6.15 and Figure 6.2 validate H13 (β = 0.115, T=1.578, p > 0.050, f^2= 0.013) that employee role clarity had no statistical significance with CIE. In contrast, statistical significance between employee role clarity and organisational performance was found as represented by H14 (β = 0.377, T=8.094, p<0.050, f^2= 0.305). Therefore, H14 was supported, while H13 was not supported. This implies that the hypotheses indicate that employee role clarity is an exogenous variable.

v) Competitive Intelligence Embeddedness

When evaluating the effect of the CIE on customer satisfaction and organisational performance, the findings from Table 6.15 and Figure 6.2 authenticate that H15 (β = 0.0711, T=15.953, p<0.050, f^2= 1.023) and H17 (β = 0.251, T=4.834, p<0.050, f^2= 0.0111) were strongly significant. Thus, providing empirical support for H15 and H17 and confirming that CIE impacts organisational performance directly and through customer satisfaction. The results have again demonstrated CIE's mediating and moderating effect on customer satisfaction.

vi) Customer Satisfaction

The impact of the customer satisfaction-related factors on organisational performance was found to be statistically significant. The findings from Table 6.15 and Figure 6.2 endorse H16 (β = 0.354, T=5.792, p<0.050, f^2= 0.198), showing that H16 was robustly supported and confirming that CIE through customer satisfaction stimulates organisational performance. The results again confirm CIE's mediating and moderating effect on customer satisfaction.

After successfully evaluating this study's hypothesis, the statical model in Figure 6.2 shows that other variables directly or indirectly impact specific relationships through mediation and moderation (Aguinis, Edwards & Bradley, 2017; Borau, El Akremi, Elgaaied-Gambier, Hamdi-Kidar, Ranchoux, 2015). The following section, therefore, presents mediation of this study's results.

6.3.2.7 Mediation Analysis

According to Aguinis et al. (2017), mediation entails the presence of an intermediary variable that conveys an antecedent variable's impact on a result. As a result, mediation incorporates a third variable that plays a role in the connection between the independent and dependent variables (Cepeda-Carrión, Nitzl, Roldán, 2017; Nitzl et al., 2016). The structural model in Figure 6.2 illustrates that CIE is the mediating variable, whereas customer satisfaction is the moderating variable.

Meanwhile, 13 latent constructs were hypothesised to influence CIE, thus affecting organisational performance and customer satisfaction. This research employed 5,000 bootstrapping procedures with a 95%, and a 2.5% error probability at each tail used to conduct a two-sided test (Cepeda-Carrión et al., 2017; Nitzl et al., 2016).

The preliminary results of the percentile bootstrapping procedure have shown the significance of the indirect effect of this study's variables. Meanwhile, mediation was confirmed since all confidence interval values for the hypothesised paths did not exhibit zero values (See Table 6.16 below). Table 6.16 only represents mediation for the selected hypothesised pathways.

Table 6.16: Mediation Analysis

Confidence Intervals Bias Corrected and Total Effect										
Hypothesis	Hypothesized Path	Original Standerdized β	Mean Standerdized β	Bias Corrected	2.5%	97.5%	STDEV	T-Statistics	P Values	Decision
H15→CS	Competitive Intelligence Embeddeness -> Customer Satisfaction	0,711	0,709	-0,002	0,615	0,789	0,045	15,953	0,000	Supported
H15→OP	Competitive Intelligence Embeddenesss -> Organisational Performance	0,503	0,502	-0,001	0,403	0,592	0,049	10,343	0,000	Supported
H16→OP	Customer Satisifaction -> Organisational Performance	0,354	0,356	0,002	0,230	0,472	0,061	5,792	0,000	Supported
H14→OP	Employee Role Clarity -> Organisational Performance	0,435	0,433	-0,002	0,322	0,549	0,057	7,595	0,000	Supported
H4→CIE	Employees -> Competitive Intelligence Embeddeness	-0,194	-0,192	0,002	-0,351	-0,060	0,074	2,631	0,009	Supported
H4→CS	Employees -> Customer Satisifaction	-0,138	-0,136	0,002	-0,249	-0,045	0,052	2,651	0,008	Supported
H4→OP	Employees -> Organisational Performance	-0,098	-0,096	0,002	-0,179	-0,032	0,038	2,591	0,010	Supported
H12→CIE	Information Provider -> Competitive Intelligence Embeddeness	0,158	0,162	0,004	0,029	0,313	0,073	2,171	0,030	Supported
H12→CS	Information Provider -> Customer Satisifaction	0,112	0,116	0,003	0,021	0,231	0,054	2,091	0,037	Supported
H12→OP	Information Provider -> Organisational Performance	0,080	0,081	0,002	0,016	0,164	0,038	2,092	0,037	Supported
H8→CIE	Information Usefulness -> Competitive Intelligence Embeddeness	0,325	0,321	-0,004	0,161	0,501	0,087	3,754	0,000	Supported
H8→CS	Information Usefulness -> Customer Satisifaction	0,231	0,227	-0,004	0,115	0,356	0,062	3,731	0,000	Supported
H8→OP	Information Usefulness -> Organisational Performance	0,163	0,161	-0,002	0,078	0,265	0,047	3,468	0,001	Supported
H1→CIE	Strategy -> Competitive Intelligence Embeddeness	0,203	0,215	0,012	0,039	0,390	0,091	2,231	0,026	Supported
H1→CS	Strategy -> Customer Satisifaction	0,144	0,153	0,008	0,028	0,278	0,065	2,232	0,026	Supported
H1→OP	Strategy -> Organisational Performance	0,102	0,108	0,006	0,021	0,199	0,046	2,206	0,027	Supported

Since the significance of the indirect effect was established, a BCa confidence interval was used to evaluate the strength of the mediator effect (Hayes & Scharkow, 2013). The significance of the indirect impact associated with path coefficients and corresponding T-values are presented in Table 6.16. Specifically, the total sum of indirect effects of the findings in Table 6.16 endorses that the mediation was robustly significant between CIE and customer satisfaction (β = 0.711, T=15.953, p<0.050).

Equally, a strong significance between CIE and organisational performance (β = 0.503, T=10.343, p<0.050), indicating full mediation between CIE and organisational performance, while customer satisfaction fully mediated the relationship between CIE and organisational performance. The indirect effect path coefficient between customer satisfaction and organisational performance (β = 0.354, T=5.792, p<0.050) was significant, demonstrating a nested mediation.

Additionally, the indirect effect path coefficient between ERC and organisational performance (β = 0.435, T=7.595, p<0.050) indicates a competitive partial mediation. The indirect effect path coefficient between employee and CIE (β = -0.194, T=2.631, p<0.050); employee and customer satisfaction (β = -0.138, T=2.651, p<0.050) as well as employee and organisational performance (β = -0.098, T=2.591, p<0.050) was significant. This outcome suggests that the indirect effect path coefficient between employees and CIE was fully moderated. In tandem, CIE complemented a partial mediation between employee and customer satisfaction and employee and organisational performance.

Moreover, the indirect effect path coefficient between information providers and CIE (β = 0.158, T=2.171, p<0.050); information providers and customer satisfaction (β = 0.112, T=2.091, p<0.050) along with information providers and organisational performance (β = 0.080, T=2.092, p<0.050) was significant. This result has revealed a full mediation effect between information providers and CIE.

Concurrently, CIE partially complemented a mediation between employees and customer satisfaction as well as employee and organisational performance. Similarly, the indirect effect path coefficient between information usefulness and CIE (β = 0.325, T=3.754, p<0.050); information usefulness and customer satisfaction (β = 0.231, T=3.731,

p<0.050), as well as information usefulness and organisational performance (β = 0.163, T=3.468, p<0.050) was significant, indicating a full mediation effect between information usefulness and CIE.

CIE, however, partially complemented a mediation between information usefulness and customer satisfaction. In addition, CIE fully mediated the relationship between information usefulness and organisational performance. The indirect effect path coefficient between strategy and CIE (β = 0.203, T=2.231, p<0.050); strategy and customer satisfaction (β = 0.144, T=2.232, p<0.050) together with strategy and organisational performance (β = 0.102, T=2.206, p<0.050) was significant, thus showing a full mediation effect between strategy and CIE.

In retrospect, CIE partially complemented a mediation between strategy and customer satisfaction. CIE also fully mediated the relationship between strategy and customer satisfaction. Overall, this study showed significance amongst all the constructs when the percentile bootstrap confidence was employed. The percentile bootstrap confidence interval is a good compromise as BCa was used to address Type-I errors and uncover the existence of mediation (Hayes & Scharkow, 2013).

6.4 Conclusion

The empirical findings of the statistical analysis of the data in this study were reported in this chapter. Precisely, this chapter presented the results of the demographic profile of the participants, descriptive and inferential statistics of the constructs' items, and the reliability validity of the research instrument. The PLS-SEM analysis included the assessment of model fit, reliability, and validity of the measurement model. The measurement model demonstrated satisfactory reliability and convergent and discriminant validity. Additionally, potential Common Method Bias that might have arisen during data collection was evaluated through the Variance Inflation Factor (VIF). The explanatory and predictive accuracy of the structural model, along with the significance of the hypothesis and path coefficients, were validated. Moreover, mediation was evaluated, resulting in the structural model revealing satisfactory results. The conclusions of the results collected in this chapter are discussed in the next chapter.

Chapter Seven: Discussion of Results

7.1 Introduction

The findings of descriptive and inferential statistics were reported in Chapter 6. The outcomes of the suggested research model for this study were provided. For data analysis and hypothesis testing, SPSS version 24.0 and SmartPLS PLS-SEM were employed.

SEM based on the PLS approach was used to assess the conceptual routes. The conclusions and discoveries reported in Chapter Six are discussed in this chapter. The significant concerns revealed in the analysis are highlighted in this chapter, which analyses and compares the findings to prior findings in similar research. The results of descriptive statistics and hypothesis testing concerning past study findings are the key topics of this chapter.

7.2 Discussions for Results Obtained from Measurement Items

This section is categorised into competitive intelligence, customer satisfaction, employee role clarity, information attributes, market factors, organisational factors, and organisational performance. The results indicated the validity and reliability components of the survey sample, and respondents expressed their own opinions on the impact of these variables on CIE.

7.2.1 Organisational Factors

The organisational factors include strategic orientation, corporate culture, and organisational commitment are unique organisational resources that are highly valued.

They help organisations achieve their stated goals, including superior performance and market leadership (Ahmed, Khuwaja, Brohi, Othman & Bin, 2018, p. 583). The organisational factors that impact CIE are leadership, strategy, structure and process, and employee capabilities. The mean scores of organisational factors were measured on a five-point scale rating to generate descriptive statistics.

The average mean values for the variables under organisational factors ranged from 3.144 to 3.838. They were above the mid-point of 3.000 out of 5.000, demonstrating that respondents agreed that these organisational factors and their related items impact CIE.

7.2.1.1 Leadership

Leadership is a dynamic process that drives employee motivation to achieve organisational goals, executing managerial tasks such as planning, organisation, and decision-making processes and guiding the employees towards fulfilling the objectives (Baig et al., 2021).

Thus, leaders must stay on track, remain motivated to succeed, and serve as role models for the rest of the organisation's personnel (Kumar & Bhatti, 2020). The perceived impact of leadership on CIE was measured. The mean scores ranged from 3.337 to 3.728, more than 3.000 out of 5.000. The overall mean score of 3.572 indicates that 71.44% of the respondents agreed that moderate leadership levels impact CIE. This result shows that the respondents perceived CI use at various levels throughout the organisation’s value chain and departments, regardless of position (Asri & Mohsin, 2020).

Chinyamurindi (2016) found that middle-management communicated information gathered from CI to top managers to assist them in making strategic decisions. CI thereby creates the needed context for leaders to be proactive, take the initiative, and, where possible, dictate the rules (Ivan, 2015). Previous research by De La Robertie (2016) found that top management support influenced the environment, knowledge management, protected intangible assets, and scanned the environment. Importantly, CI provides analytical and predictive information that reduces uncertainty to simplify decision-making processes (Sewdass, 2012).

7.2.1.2 Strategy

Strategy is about identifying and pursuing new market possibilities that address new methods of producing and providing value for consumers through delivering new goods or solutions, expanding existing product lines, and reconfiguring existing solutions (Fahey, 2007, p.5).

Measurement was conducted to determine the perceived impact of strategy on CI. The mean scores ranged from 3.580 to 3.971, more than 3.000 out of 5.000. The overall mean score of 3.838 indicates that 76.76% of the respondents agreed on high synergy levels between CI and strategy. The research findings confirm that CI contributes to the organisation's strategy while verifying the effectiveness of strategic decisions (Maritz & Du Toit, 2018).

Cavallo et al. (2020) discovered a link between CI practices and the strategy creation process at various phases. A correctly organised intelligence, therefore, signifies synergies between CI and strategy management (Du Toit & Gulwa, 2016). This result also illustrates that CI and strategy translate strategic plans into sustainable organisational performance (Adidam et al., 2012). CI begins with an existing strategy and considers how the environment will impact the plan's success (Calof et al., 2015).

CI also strengthens the strategic planning process by effectively implementing competitive strategies (Arrigo, 2016; Cavallo et al., 2020). CI thereby creates new growth opportunities. It improves the quality of the strategic planning process within organisations to ensure that they are resilient to change in the dynamic business environment (He, 2015). CI then combines competitive advantage and strategic implementation (Colakoglu, 2011).

7.2.1.3 Structure and Process

The organisational structure is the anatomy that provides a foundation for the organisation (Whang & Zhou, 2019, p. 1955). Similarly, a business process is a complete, dynamically coordinated set of logically related tasks to fulfil strategic goals (Strnadl, 2006). Structure and process were assessed for their perceived impact on CIE. The mean values of the items ranged from 3.087 to 3.522, above the mid-point of 3.000 out of 5.000. The overall mean score of 3.353 indicates that 67.06% of the respondents agreed on low levels of adequate structure and process support CIE. Concurring, Wang and Zhou (2019) concluded that the organisation's structure and business process govern the total relationship flows.

This research finding reveals that even if CI provided actionable intelligence, it is challenging to develop actionable intelligence without adequate processes (Pellissier & Nenzhelele, 2013).

Moreover, this finding corroborates Nasri's (2011) result on the process and structure, which indicated that corporations were underinvesting in the internal infrastructure needed for effective intelligence operations.

Comparably, Ncube and Ndlovu (2015) found that companies encountered considerable challenges in the application and implementation of CI due to a lack of financial resources allocated to CI activities and knowledge to execute CI procedures. In contrast, Nasri (2012) found that organisations focus on developing CI processes. This process was able to provide the organisation with a sustainable competitive advantage.

However, De Pelsmacker et al. (2005) found that SA enterprises were under-equipped and ready to implement CI successfully in terms of planning, procedure and structure, data collecting, data analysis, and, most importantly, skills development. Furthermore, De Pelsmacker et al. (2005) established that CI activities were generally centralised in the marketing and sales department rather than in a distinct department. Concurring, Ranjan and Foropon's (2021) research found that respondents admitted they did not have a clear formal structure for CI and relied on a centralised informal process.

Calof et al. (2018), on the other hand, found that centralised units and a hybrid approach, in which a centralised unit and supplementary intelligence operations existed throughout the organisation, were the two most common CI structures. Therefore, organisations experience challenges in developing intelligence (Du Toit & Muller, 2004).

Meanwhile, Pellissier and Nenzhelele (2013) concluded that CI processes include a cycle of interrelated stages influenced by decision-makers, process and structure, organisational awareness and culture, and feedback. Importantly, structure and process show the formal ways of work within the organisation, while organisational culture values reveal how things get done (Cekuls, 2015b).

7.2.1.4 Employees Capability

Employee capabilities are a set of abilities, experience, knowledge and skills that assist employees in achieving organisational outcomes (Bontis & Serenko, 2007). Employees were surveyed about their perceived capabilities to optimise CIE. The mean values of the items ranged from 3.072 to 3.272, slightly more than the mid-point of 3.000 out of 5.000. The overall mean score of 3.144 signifies that 62.88% of the respondents agreed with low levels that they knew that CI existed, but they were unsure about its usefulness.

Additionally, employees and information play a critical role in successful organisations (Hagiu & Tanascovici, 2013), and the survey findings point out that CI is available for use by many employees of an organisation (Marin & Poulter, 2004). Calof (2017a) and Calof et al. (2018) revealed that, according to similar findings, a large number of firm employees (Wright and Calof, 2006).

Research by Calof (2017a), and Calof et al. (2018) also found that most employees were aware of CI and that, on average, some participated in CI activities. Similar results reported a high percentage of company employees are both aware of and participating in CI operations (Wright and Calof, 2006).

CI integrates information throughout the organisation, whereby employees provide the information needed for intelligence efforts (Calof, 2017a). In addition, this research result suggests the absence of a culture that encourages employees to use CI for information sharing. Similarly, Cekuls' (2015b) research on implementing CI in companies indicated the trends where employees did not feel motivated to share information.

Leadership acceptance, awareness and support, employee involvement, and a competitive culture will ensure successful CI practices throughout the organisation (Saayman et al., 2008). This view is consistent with Asghari et al. (2020), whose research showed that organisations benefit from CI through culture building.

Organisational culture, along with employee involvement and buy-in in the collection and the exchange of business, enhances the dissemination of CI and information throughout the organisation (Cekuls, 2015b). The confidence between employees and leaders and

the organisational culture enriches CI within the organisation (Cekuls, 2015b). The relationships between employees, corporate training, and workplace assessment should be considered when organisations develop and implement CI (Asghari et al., 2020).

Therefore, the organisation should consider training to embed CI effectively. Strauss and Du Toit (2010b) stress that a good intelligence program is sustainable if everybody participates. Essentially, leaders should explain the importance of the CI program to the employees, and employees should be educated about possible sources of information and perceive the usefulness of the competitive information they encounter to communicate it throughout the organisation's value chain.

7.2.2 Market Factors

Uncertainty and external pressure are two important variables in the industry (Garcia-Alsina, Ortoll & Cobarsí-Morales, 2013). Customer, technology, and information providers are some market factors that affect CIE. The average mean scores for variables under market factors ranged from 3.362 to 3.775, more than 3.000 out of 5.000. This result shows that respondents agreed that market factors and related items impact CIE.

7.2.2.1 Competition

Competition probes organisations to see the possibilities in the marketplace (Sundiman, 2018). The drivers of CI in organisations include identifying competitor information, pricing policies, and product production (Asghari et al., 2020). The competition impact of CIE was measured.

The mean values of the items ranged from 3.312 to 4.261, above the mid-point of 3.000 out of 5.000. The overall mean score of 3.615 shows that 72.30% of the respondents agreed that CI provides much-needed information about the competition at moderate levels. This finding also suggests that CI provides market insights about the competition rather than competitors (Gilad, 2016). Attesting CI provides information about competitors' present and future behaviours, customers, technologies, governments, markets, and the general business environment (Yap et al., 2013b).

CI anticipates market developments, and it provides much-needed information about opportunities and threats that awaits. CI examines competitors' capabilities, intentions, actions, and vulnerabilities for organisations to anticipate any developments in the market quicker than the competition (Uzoamaka et al., 2017a).

These views reinforced Nazar and Seidali Route (2017) found that knowledge trends in the market, foreknowledge of competition, technology, and strategy had a positive and significant relationship with organisational flexibility. Additionally, Asghari et al. (2020) found that competitor information positively and significantly influenced CI.

Koriyow and Karugu (2018) found CI useful for analysing competitiveness, monitoring the external environment, and evaluating new technological developments. CI equips organisations with insights into competitors' actions and intentions (Onifade et al., 2013).

Since CI controls information and knowledge within the organisation and its network, SA insurance companies need to use CI to help them adjust their strategy to the new paradigm of competition.

7.2.2.2 Customer Insights

With increased business activity, customer insights are gaining more value to enhance business performance and achieve a competitive advantage in target markets. As customer expectations grow, organisations can obtain customer information in high volumes and variety due to increasing social media usage (Chouhury & Harrigan, 2014).

Customer insights were measured as a result of CIE. The item's mean values ranged from 3.685 to 3.862, above the mid-point of 3.000 out of 5.000. The overall mean score of 3.775 demonstrates that 75.50% of respondents agreed that organisations use CI to gain helpful customer insights at high levels.

This finding implies that CI combines data obtained from the market to arm organisations with new knowledge about competitors, customers, and suppliers (Ben Sassi et al., 2015). This view is congruent with Urbinati et al. (2019), whose research found that exchanging big data and analytics was essential for co-innovation with suppliers and customers.

CI is used to support strategic, and tactical decisions and to understand the technology environment, customers and markets (Du Toit, 2015; Vreins & Søilen, 2014). Equally, Calof et al. (2018) found that companies used intelligence gathered from CI for strategic and tactical business decisions, focusing on intelligence being dominantly on competitors and customers and innovation being among the most frequent intelligence focuses.

Similarly, Tanev and Bailetti (2008) discovered that customer and industry knowledge were positively related to inventive performance. CI creates customer value by combining the organisation's resources (Gračanin et al., 2015). The development, integration, and application of CI keep increasing customer value (Blenkhorn & Fleisher, 2001).

CI activities, therefore, scan the environment to collect intelligence about customer needs, technology and changes in the competitive environment (Ambrosini & Bowman, 2009; Teece, 2007; Woldesenbet, Ram & Jones, 2012). Adidam et al. (2012) also found that respondents perceived those customers and competitors had a significant impact on organisations, given the intense competition in markets.

Tanev and Bailetti (2008) also established that customer and company information is frequently used compared to competitor and market information. In contrast, Crayon's (2019) study found that direct and indirect competitors topped the charts regarding CI targets, but companies and customers followed closely.

Calof (2017a) also corroborated the view by finding that competitors were the most mentioned target of intelligence operations, while consumers came in second. Several organisations also researched other targets, such as suppliers, government, universities, associations, and partners.

SA insurance companies should therefore devote more time gathering customer intelligence and intelligence about the competitive markets rather than focusing solely on the competition.

7.2.2.3 Technology

Technology is vital for CI since it drives the process and can produce and disseminate information to other platforms (Almada-Lobo, 2015). Equally, technology plays a significant role in achieving market share, satisfying and meeting the needs of customers (Asghari et al., 2020). The effect of technology on CIE was assessed. The mean values of the items ranged from 3.167 to 3.630, above the mid-point of 3.000 out of 5.000.

The overall mean score of 3.362 shows that 67.24% of the respondents agreed that technology affects CIE at low levels. This result is consistent with Asghari et al. (2020), who found that information technology had a significant and positive influence on CI, while the study by Koriyow and Karugu (2018) found that CI assisted in monitoring technology, customer base, competitors, ecology, suppliers and economics.

This result shows that information technology improves the sustainability of organisations in the highly competitive global business environment (Wu et al., 2015). It is therefore essential to link technology intelligence to CI in sustaining competitiveness. This result shows that the technology position of an organisation determines its competitive advantage, innovation opportunities, and CI (Sarica et al., 2019).

Meanwhile, technological changes impact all scopes of social life (Pradhan & Jena, 2017; Madirov & Absalyamova, 2015). Bisson and Tang Tong's (2018) research results provided empirical evidence to promote training and technology adoption among companies to achieve higher CI practices.

New technologies change how intelligence is therefore gathered and disseminated throughout the organisation. Additionally, organisations with superior technology and infrastructure competencies tend to be more innovative and positively affect the performance of CI (Tahmasebifard & Wright, 2018).

To embed CI, SA insurance companies must develop technology capabilities and infrastructure that increase CI's output. This view corroborated Asghari et al. (2020), whose research showed that IT infrastructure and capability needed development to increase CI for the organisation.

SA insurance companies, therefore, need to adopt information and communications technology tools in their business processes to innovate collaboratively with their customers and suppliers worldwide (Abhari et al., 2017).

7.2.2.4 Information Providers

The introduction of big data and Web 2.0 has given businesses new options and problems obtaining CI (Sun & Wang, 2015). As a result, supplier participation in innovation processes may be a source of long-term economic advantage; for example, most technical advancements come from suppliers (Bao, 2020). The information providers had an impact on CIE. The mean values of the items ranged from 3.159 to 3.594, above the mid-point of 3.000 out of 5.000. The overall mean score of 3.456 demonstrates that 69.12% of the respondents agreed at moderate levels that information providers support CI with sourcing quality information for their organisations.

This result correlates to Sarraf and Esfahani's (2020) assessment that showed the positive impact of CI web resources and alliance with information providers in the field of CI. This result indicates that information services, corporate libraries, and research vendors are responsible for providing relevant information that answers specific questions. CI interprets information and provides management with a perspective on risks and opportunities in the market (Gilad, 2016).

Essentially, information providers have experience in dealing with database vendors. They have developed strategies and databases to source relevant information for decision-makers of an organisation (Uzohue & Yahaya, 2016).

Tanev and Bailetti’s (2008) research found that specialised suppliers had the greatest rate of utilising information about consumers and the industry compared to new technology-based and service organisations. This finding validates the notion that internet-centred information providers are progressive while traditional enterprise IT providers impede (Degerstedt, 2015b). Lemos and Porto (1998) reported that professional supplier information was the most successful in driving innovation, while consumer information is most beneficial to the innovative process.

Therefore, CI gets much of the information from experts outside the organisation and combines secondary sources outside the organisation with internal information for making strategic decisions (Calof, 2017b). Thus, CI interprets quality information sourced from web-based aggregators of information outsourced collectors for strategic decision-making (Gilad, 2016).

Similarly, Markovich et al. (2019) showed that CIE positively impacted the perceived quality of web information sources and alliances with information providers. Since CI providers focus on organised CI, information providers should meet the needs of various information users in organisations and identify various strategies such as web mining to capture big data and online resources.

In so doing, web mining can assist them in retrieving, processing and capturing information from web pages and documents on the Internet (Silva, Pacheco, Negrete, Niño, Lezama & Varela, 2019). Furthermore, information professionals need the foresight to know the most relevant sources and must pass this advice on to organisations.

In essence, information providers can help turn information into intelligence by assisting SA insurance companies in managing data and information (Diyaolu, 2019). CI will convert information obtained from web mining into knowledge about a group of competitors, which various departments within the SA insurance companies can use to make strategic decisions (Adidam et al., 2012).

7.2.3 Information Attributes

Organisations need the information to solve complex problems and make decisions that affect the present and the future (Opoku, 2015). The attributes that measure the value of the intelligence produced through a CI program include accuracy, usability, relevance, readiness and timelines (Bose, 2008).

Therefore, information attributes impacting CIE have information accuracy, credibility, quality, and usefulness. The average mean values for the information attributes ranged from 3.617 to 3.819. They were above the mid-point of 3.000 out of 5.000, showing that respondents agreed that information attributes had significantly affected CI.

7.2.3.1 Information Quality

Information quality consists of objectivity and subjectivity elements of accuracy, reliability, credibility, comprehensiveness, and transparency (Diakopoulos & Essa, 2008). Information quality, therefore, determines the quality of information developed and delivered within the organisation (Azemi et al., 2017). The perceived impact of information quality on CIE was measured. The mean values of the items ranged from 3.562 to 3.736, above the mid-point of 3.000 out of 5.000.

The overall mean score of 3.668 indicates that 73.36% of the respondents agreed that CI provides quality information throughout the organisation. This result suggests that information quality depends on the trustworthiness of its source, while every piece of data is believed valuable for some task (Talaoui & Rabetino, 2017). Notably, information is guaranteed good quality if it is trusted and valuable to connect and exchange ideas (Mai, 2013).

According to Çoklar, Yaman and Yurdakul (2017), information literacy significantly predicts online information search competencies.; therefore, it is much more meaningful to identify and filter valuable CI before the collection process than afterwards (Sun & Wang, 2015). Information quality is essential in solving problems and making effective decisions (Ottonicar, Valentim & Mosconi, 2018).

Consequently, the quality of information depends on the process, organisation, dissemination, and effective evaluation. Zhang et al. (2012) supported this notion and concluded that the collected information should be adequately processed, organised, disseminated, and evaluated to realise its value.

In their research results, Zhang et al. (2012) also found no correlation between information quality and quantity. This research result suggests that Big data and Web 2.0 collect external sources of information that make the CI gathering process extraordinarily effective and reliable at a reduced cost of CI storage and analysis (Sun & Wang, 2015).

This view shows that the internet positively impacts the quality of competitive information, affecting the organisation, thereby improving returns and effective management (Raghunathan, 1999; Teo & Choo, 2001).

Concurring, Teo and Choo (2001) discovered that external internet use and research substantially impacted the quality of CI information. Simultaneously, Teo and Choo (2001) found that the internal usage of the internet had no impact on the quality of CI information. In contrast, some studies found that web information quality significantly positively affected organisational capabilities and performance (Setia et al., 2013).

Therefore, web information sources augment the CIE capability function and provide decision support to improve organisational performance (Markovich et al., 2019). This view illustrates evidence that measurements of information quality predict organisational outcomes (Madnick, Wang, Lee & Zhu, 2009).

A recent study has shown that the relationship between information quality and organisational outcomes is systematically measurable, confirming that information quality predicts organisational outcomes (Slone, 2006). In contrast, Teo and Choo (2001) discovered empirical evidence that excellent CI information significantly influences the organisation. Similarly, Gorla et al. (2010) established that information quality positively affected organisational performance, while the impact of perceived quality and innovativeness was found (Yoo, 2014).

Since acquiring business intelligence from web information is a complex task for professionals due to the overwhelming volumes of information, SA insurance companies should make information literacy fundamental in guiding individuals to analyse the quality of these sources (Jin & Ju, 2014). Therefore, information literacy enhances the CI process since it focuses on the quality of information and its origins. For competitive firms, the link between CI and information literacy is critical (Ottonicar et al., 2018).

Importantly, CI refreshes the flow of external information before it is filtered and transformed into valuable insights and delivered to business users as a form of actionable intelligence to aid decision-making (Talaoui & Rabetino, 2017).

In addition, CI continuously updates competitors' information and generates analysed data and information integrated throughout the organisation. As the quality of data and information determines the organisation's strategic decision-making process, SA insurance companies must be able to sort and select quality information for the organisations to cope with market changes.

Moreover, SA insurance companies need to invest in a CI-specific function that translates data into meaningful insights that they can use to improve business processes and make the best decisions that will create a strategic advantage in the market.

7.2.3.2 Information Credibility

Given the immense diversity of online information, including unverified and malicious information, assessment of source credibility is crucial (Aharon, Ruban & Dubovi, 2021).

Information credibility refers to the objective evaluation of information quality, precision and measuring information sources (Zhao, Lu, Wang & Ma, 2015, p. 162). The impact of information credibility on CIE was measured. The mean values of the items ranged from 3.714 to 3.902, above the mid-point of 3.000 out of 5.000. The overall mean score of 3.819 illustrates that 76.38% of the respondents agreed that information credibility significantly influenced the effectiveness of CIE. This finding shows that web information is an excellent source to monitor CI since Web sources allow users to search for real-time information to obtain CI.

Furthermore, this finding suggests that CI monitors web information effectively if connected to some specific domain. Gupta, Kumaraguru, Castillo and Meier (2014), and Metaxas, Finn and Mustafaraj (2015) have created systems to assess information credibility automatically in real-time.

Zhao and Jin's (2011) research consistently showed that their system improved web CI's extraction effectiveness and credibility evaluation. Moreover, Zhao and Jin (2011) further demonstrated that the CI extraction module's primary job was to extract domain-constrained CI from Web sites and transmit it to the credibility evaluation module.

This result shows that it is vital to prevent the proliferation of fake or malicious information obtained from web information sources by developing techniques to verify information from any web-based information sources. Therefore, Alrubaian et al. (2016) took a different approach in their study. They applied 10-fold cross-validation over four machine learning algorithms to test information credibility on two different datasets.

This study's results revealed a significant balance between recall and precision for the tested dataset. While Erkan and Evan's (2016) research confirmed that information adoption, quality, credibility, usefulness and demands of information, and attitude toward information were essential variables of eWOM in social media that affected customers' purchase intentions. This result shows that individuals judge information credibility by evaluating its source and content (Myers, Starliper, Summers & Wood, 2017).

Meanwhile, using content and social structure in finding credible sources of information influences explicit and implicit judgements of credibility (Myers et al., 2017). Concurring, Canini, Suh and Pirolli (2011) showed that the thematic content of information sources and the structure of social networks impacted source trustworthiness.

While ODonovan, Kang, Meyer, Höllerer and Adalii's (2012) study showed that the underlying network and information flow dynamics are better credibility indicators than text content. Tormala, Briñol and Petty (2006) also found that source credibility influenced positive attitudes and generated positive thoughts amongst the people who respond to a message and then learn of the source. The above views validate previous research studies by Bamber (1983), and Petty and Cacioppo (1986) that have shown that a message's persuasiveness and perceived credibility impact a person's decision-making.

Thus, if individuals doubt the source's credibility, they tend to question the credibility of the content and the information itself (Myers et al., 2017). According to Go, You, Jung, and Shim's (2016) research, consumers' views of the reliability of online information and trust in the press were impacted by news and websites. Furthermore, this study discovered a link between confidence in the media and views of internet information's reliability.

According to this study's findings, users' perceptions of the credibility of any given information source may be regarded as an outcome in the attribution process. Therefore, credibility provides the required rationale to build trust in any situation. Since managers receive multitudes of reports and vast amounts of information from their subordinates daily, they should use perceptual filters to evaluate and decide which information is most important and valuable.

7.2.3.3 Information Accuracy

According to Stefanikova et al. (2015), information is valuable if it is relevant, accurate, and reliable. Information Accuracy refers to the validity of information obtained from a search (Jaworski, Macinnis & Kohli, 2002); thus, multiple sources communicating information about the same issue quantifies the accuracy of information (Jaworski et al., 2002). The effect of information accuracy on CIE was measured.

The mean values of the items ranged from 3.406 to 3.707, above the mid-point of 3.000 out of 5.000. The overall mean score of 3.617 demonstrates that 72.34% of the respondents agreed that CI produces accurate information from a reliable source. This result suggests that participants trust the accuracy of information if it is verifiable from a source. This finding aligns with the research findings from Wright, Eid and Fleisher (2009) that data used to produce information was accurate if it came from more than one credible source.

Gamble's (2018) results showed that participants placed greater faith in the more exact source than in the less precise source, and decision-making accuracy declined as cognitive load rose. The research results from Wright et al. (2009) also showed that respondents strongly argued that accurate information depended on where one used the information gathered.

This result suggests that the web has created a platform for a competitive source of external information. It improves the accessibility and availability of intelligent information to enrich the collection phase of CI (Leeflang et al., 2014; Reinmoeller and Ansari, 2016).

Previous research by Sewlal (2004) indicated that information provided by the web was accurate most of the time. In contrast, respondents shared the challenges of finding accurate information to analyse and share with their teams besides having access to numerous sources of information and data (Crayon, 2019). This finding demonstrates that literacy is linked to people's experiences because it reveals how they seek, assess, and produce knowledge (Demasson, Partridge & Bruce, 2016).

As SA insurance companies collect data and information quickly, they must ensure that Information is precisely appraised to give value to its top management to get a true competitive edge over market competitors (Bartes, 2014a). CI acquires appropriate and accurate information about competitor actions and plans for supporting management with effective decisions (Peltoniemi & Vuori, 2008). Hence, most executives rely on competitive intelligence information for decision support to stay ahead of the competition and make actionable decisions (Ezenwa et al., 2018).

CI integrates and structures information and knowledge that influences and promotes knowledge management in organisations (Chevallier et al., 2016). Therefore, CI integrates information throughout the organisation, enabling employees to provide the necessary information to gather market intelligence (Calof, 2017b).

7.2.3.4 Information Usefulness

With increasing volumes of data and information, organisations are experiencing an overload of information leading to the poor use of information resulting in quality becoming a benchmark for making a disparity between relevant, useable, and redundancy of information (Saxena & Lamest, 2018). The usefulness of information on CIE was measured.

The mean values of the items ranged from 3.489 to 3.812, above the mid-point of 3.000 out of 5.000. The overall mean score of 3.681 displays that 73.62% of the respondents agreed that information use impacts CI adoption throughout the organisation. This result has indicated that respondents perceived the usefulness of the competitive information

they encountered, showing that the direct benefits of CI reduce and manage the risk. It makes data reliable by providing useful information (Köseoglu et al., 2016).

This result is in line with Tseng and Wang's (2016) research, which revealed that perceived risk directly affected intentions to adopt information while perceived usefulness of information indirectly affected intentions to embrace it. This finding demonstrates that social capital promotes an individual's access to information while also improving that information's quality, relevance, and timeliness (Adler & Kwon, 2002).

In a related study, Jin et al. (2009) found that information quality and source reliability, directly and indirectly, influenced information usefulness and continuation intention. The findings also demonstrated that source credibility and dis-confirmation impacted satisfaction and inclination to continue. Similarly, Gunawan and Huarng's (2015) study found that user opinions regarding information usefulness were influenced by source trustworthiness and social influence.

Li (2013) found that two aspects of the persuasive message, source credibility and argument quality, had a substantial impact on social influence and emotional and cognitive responses. A previous study by Erkan and Evans (2016) found that information quality and credibility affected the usefulness of the information. Therefore, information collection and correct use directly impact business results (Adidam, Gajre & Kejriwal, 2009).

Concurring with this view, Souchon et al. (2003) found that decision-makers' use of information impacted organisational performance. This current research results show that organisations must comprehend and understand all the strategic information. CI is the most appropriate tool for achieving this aim (de las Heras-Rosas & Herrera, 2021).

The information climate and outwardness of the organisation dictate the circumstances that govern access to and use of information, as well as the information infrastructure deployed throughout the organisation (Correira & Wilson, 2001; Garcia-Alsina et al., 2013).

With a rapid increase in data collection, Fleisher (2008); Wong and Saunders (2020) point out that most organisations depend on web information sources because of their accessibility and relevance.

SA insurance companies should therefore integrate CI activities that present information in a valuable way to permit users to make decisions since organisational structure, culture, and openness to data sharing can inhibit or facilitate the flow of information throughout the organisation (Correira & Wilson, 2001; Garcia-Alsina et al., 2013; Leborgne-Bonassié, Coletti & Sansone, 2019; Sassanelli, Pezzotta, Pirola, Sala, Margarito, Lazoi, Corallo, Rossi & Terzi, 2018).

7.2.4 Employee Role Clarity

Job clarity is crucial for responsive performance and can considerably help organisations manage outcomes and productivity (Sangkala et al., 2016, p.5481). Role clarity relates to the amount of information available to assist employees in performing their functions effectively (Chan & Schmitt, 2000). The effect of employee role clarity on CIE was measured. The items' mean values ranged from 3.185 to 3.746, above the mid-point of 3.000 out of 5.000.

The overall mean score of 3.401 signifies that 68.02% of the respondents agreed that employee role clarity provided autonomy and clear guidelines for employees to source and store CI information. This research result indicates that employees with high role clarity or low role ambiguity know what is expected of them and have access to the resources needed to do their job obligations (Newman et al., 2015b).

This finding also implies that organisations allow employees to contribute information regularly without telling them of management's information requirements (Dishman & Calof, 2008). This research result attests to the importance of a skilled workforce in providing companies with intelligent information, showing that employee satisfaction is directly related to investments in human resources practices (Muritala et al., 2019).

Sangkala et al. (2016) also found that human resource factors positively correlated with job satisfaction, including employee training and performance appraisals.

This finding demonstrates that managers know CI elements such as employees, training, communication skills, and corporate loyalty (Hamidizadeh et al., 2014). Du Toit and Sewdass' (2015) research results indicated that SA organisations upskilled their employees to collect information on the competitive environment.

This result validates that employees are frequently better at managing and utilising CI since they are closer to the source (Hughes et al., 2013). This view aligns with the report by Gračanin et al. (2015) that employees in direct contact with customers or clients serve as the most valuable source of CI. Therefore, customer interface employees acquire more knowledge about customers, markets, and the competition (Vuori, 2011).

The organisation's salesforce is more likely to obtain competitor information since they deal with more than one organisation (Nasi & Zarai, 2013). Similarly, Du Toit and Sewdass (2015) found that SA organisations' most important primary sources were industry experts, direct consumer feedback, and employees. Calof (2017a) also found that internet websites and company employees were top secondary and primary sources of information, respectively.

Gračanin et al. (2015) similarly found that the internet and employees were proven to be CI primary information sources for all EU and Serbia companies. This result shows that role clarification guides and coordinates employee work-related activities by setting task objectives for the team (Hassan, 2013). Newman et al. (2015b) also discovered that when the positive association between ethical leadership and assisting behaviour was larger, subordinates experienced higher degrees of role clarity. Furthermore, their study showed a negative association between ethical leadership and deviant behaviour.

Therefore, leaders should foster a strong connection with employees by combining moral ideas with interpersonal interactions (Osborne & Hammound, 2017, p.53). Hence, business executives have begun to track how different interpersonal behaviours affect productivity (Hausknecht & Holwerda, 2013). They have developed high expectations and regular performance assessments to enhance employee engagement and collaboration to fulfil the organisation's objectives (Cooper-Thomas, Paterson, Stadler & Saks, 2014).

Consistent with these views, Mukherjee and Malhotra's (2006) findings supported these claims, indicating that feedback, involvement, and team support substantially impacted role clarity, work satisfaction, and organisational commitment. Furthermore, Mukherjee and Malhotra (2006) research revealed that role clarity played a critical role in explaining employee perceptions of service quality.

Importantly, role clarity assists employees with shaping their behaviour in their positions for more responsive outcomes (Sangkala et al., 2016). This view is in line with Kauppila's (2014) research which showed that employees who felt that their actions controlled work and were aware of their abilities to perform since they experienced much higher role clarity than employees who did not have these control beliefs. In addition, Kauppila (2014) discovered that the organisation's purposeful strategy-making process enhanced employee role clarity in a good way. It weakened the positive effect of general self-efficacy at the same time.

Another research by Nansubuga and Munene (2013) found a strong link between reflection and explicit competencies, emphasising the need to articulate tacit knowledge to generate exact competencies that improve role clarity. This research backs up Thangavelu and Sudhahar's (2017) analysis, which found a link between role clarity, performance feedback, and employee satisfaction on performance perception.

Muritala et al. (2019) showed that CI positively correlated with employee productivity. CI increases productivity by evaluating an employee's output in a specific period. Thus, employee satisfaction translates into an organisation's ability to attract and retain employees and achieve lesser turnover rates. Congruently, Hassan (2013) found that organisations with a high level of role definition had considerably greater levels of job satisfaction and reduced turnover rates.

The analysis of this current study shows that role ambiguity inhibits employees' abilities to perform their duties, negatively impacting organisations (Bolumole et al., 2016). Role ambiguity creates conflict amongst team inefficiencies and impacts employee productivity and organisational performance. Therefore, SA insurance companies need to shape

employees' attitudes and behaviours for responsive business performance (Fisher et al., 2010).

7.2.5 Customer Satisfaction

Customer satisfaction is an important performance metric for a company. Customer satisfaction is a key predictor of consumer purchase intentions and loyalty (Muritala et al., 2019, p.131). Customer happiness is accomplished by high-quality service, product innovation, and tailored products and services that match consumers' specific needs, resulting in customer loyalty (Hill et al., 2014).

The impact of CIE on customer satisfaction was measured. The items' mean values ranged from 3.685 to 3.848 and above the mid-point of 3.000 out of 5.000. The overall mean score of 3.764 validates that 75.28% of the respondents agreed that CIE intensifies customer satisfaction and loyalty. This finding is consistent with recent research by Sarraf and Esfahani (2020), which established that CI was an essential factor that can increase customer satisfaction, indicating that CI is a capability that fosters a positive customer experience in every state of the customer journey (Hughes et al., 2013).

Customer satisfaction is an essential facet of organisational performance because it is the growing awareness that consumers contribute to creating value for companies (Gomez et al., 2004). This view is consistent with Afolabi and Adegoke's (2014) findings that customer satisfaction was a significant differentiator in achieving organisational profits. Calof (2017a), and Calof et al. (2018) found that CI was the most frequently used metric to measure customer satisfaction.

For that reason, Markovich et al. (2019) discovered that CI positively affected customer satisfaction but did not directly impact performance. In contrast, post-analysis showed the mediating effect of CI on customer satisfaction. Equally, Afolabi and Adegoke (2014) concluded that customer satisfaction contributed to the organisation's profit through CI.

Therefore, CI provides a general screening of the corporate environment, yet, its primary purpose is to improve its competitive position, as it puts the customer's CI at the centre of attention (Hughes et al., 2013).

In addition, CI increases customer satisfaction, resulting in high sales and profitability for the organisation. Curtis et al. (2011) discovered that commitment and repurchase intention have a significant positive relationship. Similarly, Sohaib et al. (2016) found a link between satisfaction and repurchase intentions, trust, and commitment.

This finding demonstrates that organisations with high customer satisfaction rely on close customer relationships, which help to build the company's reputation over time (Anderson & Yu, 2016). Moreover, this finding suggests that increasing customer satisfaction, repurchase rates, and loyalty formation positively influence organisational performance and lead to a competitive advantage (Curtis et al., 2011).

Customer satisfaction enhances loyalty and the company's profitability (Sohaib et al., 2016). This viewpoint is consistent with past study findings, which found that customer happiness influenced several areas of financial success (Anderson et al., 2004; Ittner & Larcker,1998). Similarly, Banker and Mashruwala (2007) discovered that customer satisfaction impacted various factors, including a company's future performance.

With CI providing market information, CI inspires customer satisfaction, sequentially enhancing the organisation's profitability (Afolabi & Adegoke, 2014). Consistent with this view, Hughes et al. (2013) research demonstrated value in gathering and using CI at the tactical level for customer interface. CI objectives, quality of intelligence, and delivery of intelligence on time are the critical drivers for overall customer satisfaction (Kruger, 2003). Therefore, SA insurance companies should leverage customer service to attract and retain customers, along with improving customer relationships over time.

7.2.6 Organisational Performance

Organisational performance involves analysing a company's performance against its objects and goals. For instance, organisational performance comprises actual results or outputs compared with intended outcomes (Irenaus, Ikechukwu & Ndubuisi, 2021,p. 47).

Organisational performance refers to an organisation's actual results compared to its expected outputs (Tomal & Jones, 2015). The impact of CIE on organisational performance was appraised.

The mean values of the items ranged from 3.236 to 3.721, above the mid-point of 3.000 out of 5.000. The overall mean score of 3.552 indicates that 71.04% of the respondents agreed that CI inspires productivity and organisational performance.

This finding is in line with Waithaka (2016), whose research showed that CI practices had a favourable and statistically significant impact on staff productivity and financial performance of enterprises listed on the Nairobi Securities Exchange. Equally, Waithaka et al. (2016) showed that target-oriented CI practices had a positive and statistically significant relationship with the performance of organisations listed in the Nairobi securities exchange.

In concurrence, Akram and Waheed (2012) found a significant positive correlation between CI and organisational performance. Similarly, Sepahvand et al. (2016) showed a positive and significant effect of CI on organisational performance.

Sepahvand et al. (2016) also found orientation to impact organisational performance positively. A positive role of the mediator is therefore responsible for organisational performance and CI. Therefore, SA insurance companies need to entrench CI in their business practices to gather market insights and sustain performance.

7.2.7 Competitive Intelligence Embeddedness

CI is a process that involves examining and observing the market to gather and share actionable intelligence to create a competitive advantage for organisations (Kim et al., 2016,p. 44). The effect of CI on the organisation was appraised. The mean values of items ranged from 3.804 to 4.029 and were above the mid-point of 3.000 out of 5.000.

The overall mean score of 3.912 illustrates that 78.30% of the respondents agreed that CI scans respond effectively to changes in the competitive environment. This result correlates with De Pelsmacker et al. (2005), who showed that organisations that used CI amongst Belgian and SA exporters could anticipate opportunities and threats in the competitive environment.

Also, Dishman and Calof (2008) found that the CI practices effectively collected information. Meanwhile, CI plays an essential role in tracing and analysing intelligent information for organisations to respond to the external and internal environments (Calof et al., 2015).

This view authenticates that CI is a strategic management tool that scans the environment to gather and disseminate intelligent information. It also analyses market trends for effective decision-making processes (Amiri et al.,2017; Bartes, 2014b; Pellissier & Kruger, 2011; Sewdass & Du Toit, 2014). Moreover, CI is a strategic management instrument that assists management decisions (Chevallier et al., 2016, p.1192).

CI is a tool that supports organisations to gain a competitive advantage to outstrip competition (Ahmed et al., 2014). Consistent with these views, Hemmatfar et al. (2010) found that strategic information systems aided competitive advantage in organisations and contributed to strategic goals, thereby significantly increasing performance and productivity. This result proves that CI gathers, analyses, and fulfils the role of transferring intelligence concerning competitors, customers, and products (Mabe et al., 2019).

In effect, CI transforms competitor information into actionable insights that allow organisations to adjust their plans to stay ahead of the competition (Tuan, 2016). Therefore, information must flow easily across organisational boundaries to execute the corporate strategy and improve organisational agility (Neilson et al., 2008).

Al-Zu'bi (2016) recommended that managers be conversant and know how to evaluate and identify organisational agility to accomplish organisational goals. In essence, CI enables organisations to benchmark their performance against the competition and focus on improving efficiencies, scale, and coordination to outperform peers (Bose, 2008; Sanderson, 2013b). This view aligns with the findings from Calof et al. (2018) that CI often contributed to strategic analysis and decisions. In addition, CI contributed to setting marketing objectives, implementation, and control. For that reason, a study by Charity and Joseph (2013) found a significant relationship between CI and strategic advantage. CI affects decision-making and significantly impacts the organisation's operation and performance (Ahearne et al., 2013).

Ching and Zabid (2017) also found that management used CI for strategic decision-making about sources of information obtained from customers, competitors, newspapers and periodicals, intranet and extranet, and industry associations.

In contrast, previous research by Köseoglu et al. (2016) showed that managers only used CI for planned activities instead of strategic resolutions. This result indicates that CI creates a competitive advantage when the entire organisation and its networks are committed to developing practical insights (Calof & Wright, 2008). CI is influenced by decision makers' awareness and acceptance of CI practices and a competitive culture such as employee engagement and management support that creates legitimacy and importance (Saayman et al., 2008). This view supports Dishman and Calof's (2008) model demonstrating that CI processes produce desired outcomes when supported by organisational culture, awareness, and structures.

As a result, Du Toit (2013) recommended that employee awareness, training, and culture that embraces CI intelligence activities are much needed for SA organisations to compete globally. For organisations to reap the benefits of CI, leaders of the SA insurance companies need to create greater awareness and a culture of competitiveness.

Leaders of the SA insurance companies should foster an organisational culture that embeds CI activities to ensure that they are supported and used throughout the organisation. In that way, employees will be made aware of the importance of information about competitors and have the skill to identify critical issues arising from competitors.

7.3 Discussions for Hypotheses Testing

The previous section discussed results obtained from the measurement items of this study. This section discusses the results obtained from testing the hypotheses formulated for the study. As for hypothesis testing, the predictive precision of PLS-SEM accepted eight out of the 17 hypothesised relationships and thereby rejected nine hypotheses. The following subsections discuss the results of this study's hypotheses.

7.3.1 Organisational Factors

The organisational factors comprise the size, quality and characteristics of an organisation's resources, employees, communication between employees, the size of the organisation, and the availability of slack resources (Duh & Fabiao, 2018).

According to Angeles (2014), the managerial structure's complexity and the quality of the human resources are the organisational factors that drive adoption. Employees' capabilities, leadership, strategy, structure, and process represent the internal factors influencing CIE adoption and implementation. The following subsections discuss the results of the hypothesis tests that have a bearing on organisational factors.

7.3.1.1 Strategy

The need for speed and agility post-COVID-19 pandemic has increased the integration of CI and strategy. The capacity of an organisation to pick and retrieve relevant data and information has a substantial beneficial influence on the creation of its strategy (Sundiman, 2018). The hypothesised path between strategy and CIE showed that strategy significantly impacted CIE. In this sense, H1 ($\beta = 0.203$, $T=2.231$, $p <0.050$, $f^2= 0.048$), which states strategy contributes positively to competitive intelligence embeddedness was supported.

This finding supports Maritz and Du Toit's (2018) research that strategy and CI were inseparable. Cavallo et al. (2020) provided empirical data on the linkage and usage of CI techniques throughout each step of the strategy creation process, which supports this finding.

Previous research by Yap et al. (2013b) has also shown that CI is essential for supporting strategic decision-making and strategic planning and identifying opportunities and threats. CI produces intelligence that helps decision-makers formulate strategies and make clear choices (Mohsin et al., 2015). Furthermore, CI equips organisations with a competitive strategy. CI also provides intelligent information on which executives can make strategic decisions (Maune, 2014a).

Yin's (2018) study reported that an executive information system with integrated CI activities would enhance the performance of the organisational strategy. In addition, Calof et al. (2018) also found that CI contributed to strategic analysis and decisions, setting marketing objectives and implementation and control. This finding attests to CI activities linked to strategic planning processes.

In tandem, CI contributes to the organisation's strategy while verifying the effectiveness of strategic decisions (Maritz & Du Toit, 2018). Equally, Maritz and Du Toit (2018) found that CI did not overlap with strategy when linked explicitly to knowledge management or marketing disciplines. Shujahat et al. (2017) revealed synergic and separate uses of knowledge, and CI, resulting in effective decisions leading to competitive advantage.

In contrast, Bartes (2014c) found that the outputs of CI were applicable most in operational management and primarily unsuitable for strategic management. This finding corroborates with Köseoglu et al. (2016), who found that there was no connection between CI activities and strategic planning and competitive position—citing that the majority of these managers were trained on tactics to gather competitor intelligence.

Furthermore, Köseoglu et al. (2016) research showed that managers only used CI for planned activities instead of strategic resolutions. Petrişor and Străin (2013) found that it was not easy to identify any aspect of the company's activity that does not have a benefit due to the use of CI.

Additionally, Petrişor and Străin (2013) concluded that CI had supported management in making better-documented decisions with incredible speed and confidence. Ding (2009) also revealed that CI has a significant role in today's commercial management and found that commercial management crucially needs CI. Therefore, SA insurance companies must embed CI in their respective organisations to implement and monitor their business strategies.

7.3.1.2 Leadership

Leadership is a social influence mechanism that optimises the efforts of others in pursuing a common goal (Kruse, 2013). Therefore, leadership is the ability to influence people's behaviour. It concerns using non-coercive means to obtain coerced participation and aiming to achieve objectives (Ivan, 2015). The hypothesised path between leadership and CIE showed that leadership and CIE were statistically insignificant.

Consequently, rejecting H2 (β = -0.081, T=1.092, p >0.050, f^2= 0.006), which states that leadership commitment and support has a positive influence on competitive intelligence embeddedness. This study contradicts De Almeida et al. (2016), who found that senior management support for CI procedures connected positively with tracker intrinsic motivation.

Furthermore, this finding shows a lack of culture among the SA insurance companies to drive knowledge sharing and embrace CI practices. Köseoglu et al. (2016) have also demonstrated a lack of awareness and knowledge of CI among hotel managers. CI awareness and culture, on the other hand, had the greatest impact on competitive advantage (Amiri et al., 2017).

Moreover, Amiri et al. (2017) have also suggested that organisations develop the CI culture by increasing awareness among the staff and offering CI training sessions for new staff. Fatti and Du Toit's (2013) findings also suggested a sustainable commitment to the principles and practices of CI. Moreover, they confirmed that enhancing a CI culture through organisations seems lacking.

Similarly, a study by Pham, Mai, Misra, Crawford and Soto (2016) found that culture is important in ensuring success in a BI system, where CI is a subset of BI. CI is also a subset of BI. Chaubey and Sahoo (2021) also found that the top leaders' commitment influenced BI's assimilation via acceptance and optimisation.

In addition, De Almeida et al. (2016) proved the relevance of inspiring knowledge-sharing behaviour through information system support, top management support, and information feedback. Meanwhile, Fatti and Du Toit (2013) found that most respondents thought their

organisations had a culture of information sharing and a collaborative atmosphere on competitive concerns.

Concurring, Asri and Mohsin (2020) showed that respondents perceived CI was being used at various levels throughout the organisation's value chain and departments, regardless of position. Equally, Chinyamurindi (2016) showed that middle-management communicated information gathered from CI to top managers to assist them in making strategic decisions. Therefore, CI creates the context for leaders to take proactive actions and dictate the rules. It provides analytical and predictive information that simplifies decision-making processes (Ivan, 2015).

Relatedly, De La Robertie (2016) found that top management support influenced the environment, knowledge management, protected intangible assets and scanned the environment. CI provides analytical and predictive information that reduces uncertainty and simplifies decision-making processes (Sewdass, 2012).

Therefore, leaders of SA insurance companies need to control information about the team's environment regardless of their leadership style. In essence, CI creates the required context for leaders to be proactive, take the initiative, and, where possible, dictate the rules (Ivan, 2015).

7.3.1.3 Structure and Process

The organisational structure and processes guide almost everything the company does, from CI, strategic planning, hiring employees and taking care of customers. Therefore, structure and process shape the formal ways of work within the organisation, while organisational culture values reveal how things get done (Cekuls, 2015b).

The hypothesised path between structure and process and CIE showed insignificance statistically. In this sense rejecting H3 ($\beta = 0.118$, $T=1.273$, $p < 0.050$, $f^2 = 0.008$), which states that structure and process have a positive influence on competitive intelligence embeddedness. This result supports Viviers, Saayman, Muller and Calof's (2002) findings that SA enterprises lacked the necessary capabilities to perform sound intelligence activities, particularly in process and structure, analysis, and awareness.

This result correlates with Dishman and Calof's (2008) study, which found that the CI practices effectively collected information but were ineffective regarding process capability and performing analysis.

Lackman, Saban, and Lanasa (2000) research found that most companies did not use an organisational structure supporting CI. Furthermore, they established that the CI function resided in the marketing, marketing research, or sales departments. Similarly, De Pelsmacker et al. (2005) found that CI activities were not organised and separated but primarily centralised in the marketing and sales department. Also, Adidam et al. (2008) showed that most CI tasks resided in the corporate planning department, with only three samples having a specialised CI department.

Concurring, Yap and Rashid (2011), and Yap et al. (2013b) found that more than half of the surveyed organisations had a formal CI unit in the marketing, market research, or corporate planning departments. Furthermore, their study revealed that these units had been in place for 5 to 9 years, with an average of 2 to 5 full-time individuals in charge of CI activities.

Nasri's (2011) research also found that businesses underinvested in the internal infrastructure needed for CI effectiveness. Furthermore, this study reported that CI activities were conducted, when necessary, with employees responsible for gathering intelligent information. However, employees did not have convenient ways to report intelligence input. Equally, Prinsloo (2016) discovered that CI efforts were primarily informal and conducted with different degrees of effectiveness across the organisation.

Prinsloo's (2016) study indicated that the company's existing information function was not utilised for CI activities. In addition, the company relied heavily on employees and a network of peers as sources of information.

Ranjan and Foropon (2021) also found that respondents admitted they did not have a clear structure for CI and relied on a centralised informal process. Calof et al. (2018) also found that centralised units and a hybrid approach were the two most common CI structures for sourcing CI information throughout the organisation.

In contrast, Nasri (2012) found that organisations developed CI processes assisting organisations in attaining sustainable competitive advantage. This result aligns with Calof and Sewdass (2020), who discovered strong connections between several CI processes, structural factors, and innovation. Calof and Sewdass (2020) also revealed which aspects of the CI process and organisation are closely linked to innovation.

In addition, research by Cekuls (2015b) found a substantial positive link between the sections " information and culture" and "process and structure" in his investigation. These results illustrate that culture is integral in entrenching CI processes within the organisation. Cekuls (2015b) found a substantial positive link between the sections "information and culture" and "process and structure" in his investigation.

These findings show that culture is critical to enforcing CI practices. SA insurance companies will therefore struggle to embed CI practices if they don't have adequate intelligence processes and structures, including visible top management support and their utilisation of intelligence (Du Toit & Muller, 2004; Nasri, 2011).

7.3.1.4 Employees Capability

Organisations' employees are important CI sources since they acquire knowledge and intelligence about competitor activities and customers. Because they are closer to the source, employees are frequently better equipped to gather and apply CI more efficiently(Hughes et al., 2013, p.103). Therefore, it is vital that employees who gather this intelligence shares their knowledge with others to increase organisational innovation (Nemutanzhela & Iyamu, 2011).

The hypothesised path between employee capabilities and CIE showed statistical significance. As a result, H4 (β = -0.194, T=2.631, p <0.050, f^2= 0.030) stated that employee capability leads to competitive intelligence embeddedness was supported. This result corroborates Cekuls (2015a), whose study showed that employees regularly provided their superiors with information on the competitive environment. Also, this result indicates that employees are actively involved in CI activities and that CI is available for use by many employees in organisations (Marin & Poulter, 2004).

Calof (2017a), Calof et al. (2018), and Calof and Sewdass (2020) found that most employees were aware of CI, and on average, some participated in CI activities. Wright and Calof (2006) also reported a high percentage of company employees being aware of and involved in CI activities. This current study's result demonstrates that SA insurance companies' employees are capable and motivated to gather intelligent information for their respective organisations.

Concurring, Prescott and Smith (1989) found that all personnel in the organisation were useful intelligence agents, and this outcome supports their results. Similarly, Nasri (2011) showed that some companies have employees that routinely provide information without being told about management's information needs, with just a few companies claiming that they have addressed the sort of information that needs sourcing with their employees.

Furthermore, Fatti and Du Toit (2013) showed that employees in competitor organisations collected information, indicating that the respondents used ethical ways to collect primary information. Ezenwa et al. (2018) also found a significant relationship between human intelligence networks and employee loyalty in the manufacturing firm.

The study on the application of CI management in businesses, on the other hand, found that employees in Latvian businesses lacked the desire to share information (Cekuls, 2015b). De Almeida et al. (2016) showed that relationships between employees and others involved in the CI process correlated positively with intrinsic motivation.

These results validate that the organisation's culture and the employees' understanding of collecting and exchanging business information play a fundamental role in accomplishing CI and disseminating information (Cekuls, 2015b).

Since employee capabilities are vital to the success of an organisation, SA insurance companies should invest in their employees to ensure that they acquire the appropriate skills needed to source competitor information seamlessly.

7.3.2 Information Attributes

The organisation's information climate consists of factors influencing access and use of information, such as the information infrastructure in place (Correia & Wilson, 2001). Information attributes such as accuracy, credibility, quality, and usefulness improve the adoption and implementation of competitive intelligence embeddedness. The following subsections discuss the results of the hypothesis tests from these information attributes.

7.3.2.1 Information Quality

The key cue of information received by a message receiver, impacting the customers' attitude shift, information adoption, and behavioural intentions, is information quality (Hussain, Song & Niu, 2020, p. 6). Thus, information quality is vital in distinguishing between usable and additional information (Saxena & Lamest, 2018). Information quality determines the quality of information developed and delivered within the organisation (Azemi et al., 2017).

The hypothesised path between information quality and CIE showed statistical insignificance. In this sense, H5 ($\beta = 0.028$, $T=0.296$, $p >0.050$, $f^2= 0.000$) stated that the quality of competitive information had a positive impact on competitive intelligence embeddedness was not supported. In contrast, an SEM AMOS research study by Markovich et al. (2019) found that the perceived quality of web information resources positively correlated with CIE. Maune (2014a) also concluded that the internet as a source of information for CI positively impacted the quality of CI.

Similarly, Teo and Choo (2001) discovered a link between using the internet for research and the quality of CI information. In tandem, Teo and Choo (2001) discovered that using the internet for internal cooperation and distribution did not affect the quality of CI information. This result suggests that information amplifies CI, so information quality impacts its implementation (Sarraf & Esfahani, 2020).

Web information sources augment the CIE capability function and provide decision support to improve organisational performance (Markovich et al., 2019). This viewpoint is consistent with Ho's (2008) findings that the perceived quality of online competitive

information sources and management's action-oriented utilisation of that information influenced the CIE capabilities and performance of the organisation.

Similarly, Setia et al. (2013) found a direct relationship between web information quality and organisational capabilities and performance. Gorla et al. (2010) also showed that information quality positively impacted organisational performance, while the impact of perceived quality and innovativeness was found (Yoo, 2014). Therefore, CI assists organisations in developing a competitive advantage when the entire organisation and its networks commit to developing actionable insights.

With organisations relying on information retrieved from web information resources, SA insurance companies need to create formal structures and processes to accommodate CI-specific functions in their operation so that this capability can translate information into unique know-how.

Organisations are developing their analytical capabilities by maintaining an internal unit dedicated to analysing, collecting, and disseminating web information (Markovich et al., 2019). Inevitably, web information sources provide opportunities and threats arising from increased volumes of information, creating an overflow that often mixes information of different quality levels.

Markovich et al. (2019) found that information overflow interferes with firms' decision-making abilities and may impact organisational performance. For that reason, Nenzhelele's (2015) conclusion was that most organisations were clueless concerning CI quality assurance.

As information overload results in some of it not being relevant and challenging for users to extract, organisations should invest in a capability that refines this information to support decisions (Markovich et al., 2019). Therefore, organisations must develop a screening process to prevent information overflow (Sarraf & Esfahani, 2020).

7.3.2.2 Information Credibility

The degree to which the communicator's statement is trustworthy, information source credibility corresponds to peripheral signals of information recipients as a reputable source (Hussain et al., 2020, p. 6). Information is plausible only if providers can influence such information from a competent and trustworthy source, resulting in information acceptance (Cheong & Morrison, 2008).

The hypothesised path between information credibility and CIE showed statistical insignificance. As a result, H6 (β = 0.183, T=1.899, p >0.050, f^2= 0.017) stated that the credibility of competitive information has a positive impact on competitive intelligence embeddedness was not supported. This result points to the inability of SA insurance companies CI's unit to source credible information and disorganised data during the collection process. This view is consistent with Maungwa and Fourie (2018a), who found that a lack of conceptual understanding of underlying CI processes and the articulation and expression of intelligence needs within CI activities attributed to CI failures.

Concurring, Herring (1999) pointed out that irrespective of the CI activity involved, the integrity and credibility of the CI unit is the critical element in the identification of the intelligence needs of the organisation. This viewpoint aligns with Bose (2008), who stated that the primary goal of a CI system is to provide reliable and usable information and data regarding key market competitiveness indicators that would aid organisations in gaining a competitive edge.

Congruent with this view, Jasima, Sulaimanb and Zakuanc (2020) showed that CI could be utilised as an antecedent of organisational performance. Therefore, the main task of knowledge-based organisations is managing the organisation's mental and intellectual capital. Because customers rely on other people's online knowledge, participation, information reliability, and information quality are essential sources that appeal to consumers' social bonds as positive or negative eWOM (Plotkina & Munzel, 2016).

However, users consider web information credible without counterchecking it against other sources (Shah & Ravana, 2014). This view correlates with Flanagin and Metzger's

(2000) study, which showed that users relied more on web-based information despite being false and biased by the type of information sought.

Jamal, Othman, Saleh, Nurhanay and Rohmah (2021) also found that transparency correlated positively with the trustworthiness of information. Furthermore, the study by Jamal et al. (2021) showed that website's ability had no impact on the integrity of information.

In contrast, Li and Suh (2015) showed that a message's competency and reliability were the key factors driving the sincerity of information. These results illustrate that web users experience difficulties verifying information due to the fluctuation of information credibility each time (Jamal et al., 2021; Shah & Ravana, 2014). The findings of Shah, Ravana, Hamid and Ismail (2015) demonstrated that when analysing the credibility of a website, using more than one technique makes gauging credibility evaluation simpler.

For that reason, Gupta et al. (2014), and Metaxas et al. (2015) created systems that assessed information credibility automatically in real-time. Similarly, Zhao and Jin (2011) showed that their system improved web CI's extraction effectiveness and credibility evaluation. This result attests to the notion that only organisations with developed intelligence networks are not only able to survive, they also gain an advantage (Kunle, Akanbi & Ismail, 2017).

As customers interact with web resources, they seek information about products or services. They trust the credibility of information, influencing their opinions and behaviours (Hussain et al., 2020). Gunawan and Huarng (2015) similarly found that source credibility and social influence affected behavioural intentions. In tandem, behavioural intentions were associated with subjective norms, while perceived risk negatively influenced behavioural intention.

Additionally, Tseng and Wang (2016) showed that argument quality and source credibility affected consumers' intentions to adopt information utilising perceived usefulness. These results illustrate that information credibility is vital for organisations since it is used as one of the drivers to monitor the realisation of strategy.

Since information trustworthiness about an organisation adds value, it accelerates trust and increases customer satisfaction and loyalty (Jamal et al., 2021). This view corroborates Diakopoulos and Essa (2008), whose study found that credibility was closely related to trustworthiness and information quality. Therefore, SA insurance companies need to embed an intelligent system that monitors consumer behaviour when interacting with web information sources.

7.3.2.3 Information Accuracy

The concordance of the information presented with the best evidence is known as accuracy. It provides key facts to explain a subject without inaccurate or misleading information (Storino et al., 2016, p. 832). The hypothesised path between information credibility and CIE showed statistical insignificance. Consequently, H7(β = -0.071, T=0.688, p >0.050, f^2= 0.003) stated that the accuracy of competitive information had a positive impact on competitive intelligence embeddedness was not supported. This result aligns with Markovich et al. (2019), who found that information accuracy had no statistically significant relation with competitive intelligence embeddedness.

The purpose of a CI program is to gather relevant information that is valid and accurate. This result illustrates that incomplete information jeopardises the organisation's CI efforts (Sewlal, 2004). Markovich et al. (2019) showed that information inaccuracy negatively correlated with CIE. Notably, inaccurate information impacts corporate strategy negatively if users misunderstand it (Bettis-Outland, 1999).

Since CI specialists are in charge of creating programs that drive information needs, they should gather, analyse, and process data providing actionable insights supporting the organisation's strategy (Du Toit, 2015; Jeong & Yoon, 2017).

Therefore, CI professionals in SA insurance companies need to filter the information during acquisition to prevent the inaccurate flow of information across the organisation. In so doing, methods, processes, and strategies customised for the information activities inherent in CI, as well as the environment in which CI appears, should be considered by CI specialists to minimise failures (Maungwa & Fourie, 2018b).

7.3.2.4 Information Usefulness

Information use allows the development and creation of competitive advantage for most organisations; hence, organisations that exploit the use of information effectively remain competitive (Araminde & Adebisi, 2018). The hypothesised path between information usefulness and CIE endorsed statistical significance between information usefulness and CIE supporting H8 (β = 0.325, T=3.754, p <0.050, f^2= 0.064), which states that the usefulness of competitive information has a positive impact on competitive intelligence embeddedness.

This result corresponds with Itani et al. (2017), who showed a correlation between social media use and CI collection. Equally, a study by Aramide and Adebisi (2018) established a connection between CI and organisational information. Furthermore, Araminde and Adebisi's (2018) study identified that adequate information use was an integral part of coping with challenges organisations face to enhance their performance and productivity.

Likewise, Souchon et al. (2003) found that information use correlated with organisational performance. In contrast, research by Markovich et al. (2019) showed no significant impact on CIE for information used politically. Erkan and Evans (2016) also found that information quality and credibility affected the usefulness of the information.

A study by Hussain et al. (2020) found that quality and trustworthiness had a substantial positive impact on information usefulness, whereas engagement negatively impacted information usefulness. These findings imply that CEOs of South African insurance firms should recognise the relevance of CI and give sufficient resources or money to the intelligence unit's operation to avoid improper information management and use (Aramide & Adebisi, 2018).

The allocation of resources dedicated to a CI function will assist SA insurance companies with reviewing competitive information to prevent irrelevant data from being distributed throughout the organisation (Gilad, 2015a).

7.3.4 Market Factors

The macro-environment consists of external forces shaping and dictating how the industry develops (Duh & Fabiao, 2018). In essence, the macro-environment consists of various stakeholders, such as industry members, customers' insights, competitors, suppliers and communities (Angeles, 2014). The following subsections discuss the hypothesis testing results that impact market factors.

7.3.4.1 Competition

The concept of competition is broad since it assists organisations in moving beyond industries and closer to the ecosystems (Iansiti & Euchner, 2018). Therefore, competition in the digital age helps organisations to exploit opportunities and possibilities in the marketplace (Sundiman, 2018).

Organisations continue to develop advanced analytical capabilities to capture market information (Sundiman, 2018). Therefore, organisations should make better use of CI to assess market dynamics (Jamil, 2013; Pargaonkar, 2016). The hypothesised path between competition and CIE showed statistical insignificance. In this sense, H9 (β = 0.082, T=1.126, p > 0.050, f^2= 0.005) which states that competitor information is positively influenced by competitive intelligence embeddedness was not supported.

This research result is inconsistent with Asghari et al. (2020), whose study found that competitor information positively and significantly influenced CI. In addition, Koriyow and Karugu (2018) discovered that CI was useful in analysing competitiveness, monitoring the external environment, detecting political and regulatory difficulties, recognising economic trends, and evaluating new technological breakthroughs.

Equally, Prinsloo's (2016) study confirmed that CI-supported businesses must keep ahead of the competition by obtaining, analysing, and disseminating data about clients, rivals, partners, or related sectors, as well as external market conditions. In addition, Tarek, Adel and Sami (2016) found that innovation and the preservation of information assets mediated and moderated the link between business intelligence and SMEs' worldwide competitiveness.

Given that CI provides organisations with insights into competitors' actions and intentions, organisations need to be proactive and use CI to neutralize potential threats and defend their market share. CI permits organisations to anticipate dynamic change and exploit various opportunities (Sundiman, 2018).

This view correlates with de las Heras-Rosas and Herrera's (2021), findings that CI ensures that organisations grasp the business and industry environment to learn from competitors' corporate and business strategies continuously. SA insurance companies must therefore be effective and proactive in identifying and responding to the operational environment's challenges, opportunities, and risks (Calof & Sewdass, 2020).

7.3.4.2 Customer Insights

With increased business activities, customer demand influences innovation, and it drives organisations to introduce new products and services and improve existing technology (Bao, 2020). In so doing, organisations are constantly looking for ways of increasing their customer base through the satisfaction of customers with their products or services (Odunlami et al., 2013). CI fulfils the role of transferring intelligence concerning competitors, customers and products (Mabe et al., 2019).

The hypothesised path between customer insights and CIE showed statistical insignificance. Consequently, H10 ($\beta = 0.111$, $T=1.538$, $p > 0.050$, $f^2 = 0.010$), which states that customer insights is positively influenced by competitive intelligence embeddedness was not endorsed. Yet, organisations can gain more value from customer insights to enhance business performances and achieve competitive advantages (Bashir, Papamichail & Malik, 2017).

Sepahvand et al. (2016) suggested that customer information should be analysed to identify customer needs and improve organisational performance. Noticeably, CI has been perceived to serve customer needs better and anticipate new business opportunities (Adidam et al., 2008). Besides, this result is inconsistent with Du Toit and Sewdass (2014a), whose study revealed that organisations used CI to gather competitive information and customer feedback.

Oyomo (2019) used Spearman and Friedman tests to show that customer-centricity and its dimensions significantly impacted CI, with customer life being the most important, as the Entropy method suggested. Concurring, Amarouche, Benbrahim and Kassou (2015) found the importance of CI among the data analysed from customer opinions.

A previous study by Pellissier and Kruger (2011) showed that prominent organisations used CI for strategic decisions and insights into customer analytics and markets. Equally, Calof et al. (2018) found that organisations utilised CI to make strategic and tactical business choices, with intelligent data outperforming competitors and customers, and that companies used CI to innovate. Bao (2020) found that customer CI significantly affected exploratory service innovation.

Similarly, Calof and Sewdass's (2020) results indicated that innovation correlated with CI activities focusing on customers, suppliers, and technology in the longer term. Furthermore, Calof and Sewdass (2020) reported that customer and technology were associated with innovation within the terrains of new products or services, strategy, and customer satisfaction among the CI evaluation performance measures.

Tanev and Bailetti (2008) also found that customer and industry information were positively connected with creative performance. Adidam et al. (2008) likewise showed that the customer sector had the most effect on organisations and the greatest unpredictability, followed by rivals, international, and economic sectors. However, most organisations spend considerable time focusing on the competitor sector rather than customers.

Likewise, Adidam et al. (2012) found that respondents perceived that customers and competitors had a significant impact on organisations, given the intense competition in markets. Tanev and Bailetti (2008) identified that customer and company information was mainly used compared to competitor and market information. In contrast, Crayon's (2019) study found that direct and indirect competitors topped the charts regarding CI targets, but companies and customers followed closely. Similarly, Calof (2017a) found that competitors were the most frequently mentioned element of intelligence efforts, followed by customers and other organisations.

Some studies have also found that rating and review numbers influenced customers' buying decisions and company owners' market views, profitability, and satisfaction (Bai, Marsden, Ross Jr and Wang,2017; Nieto, Hernández-Maestro and Muñoz-Gallego, 2014).

Given that CI transforms valuable information and data into intelligence about customers and the competition, organisations need to gather customer intelligence about the competitive markets rather than focusing solely on the competition. SA insurance companies should therefore engage more with their customers through product opinions and reviews because data coming from customer opinions and reviews are an essential information source for CI (Amarouche et al., 2015; Xu, Liao, Li & Song, 2011).

7.3.4.3 Technology

Knowledge and technology inspire innovation and allow organisations to enhance various products and services at reduced costs (Asghari et al., 2020). Organisations with superior infrastructure competencies are famous for being innovative and performing better than their peers (Tahmasebifard & Wright, 2018). The hypothesised path between technology and CIE showed statistical insignificance.

In this sense, H11 (β = -0.099, T=1.169, p >0.050, f^2= 0.009) asserts that technology readiness is positively influenced by competitive intelligence embeddedness was not supported. This finding corroborates Bisson and Tang Tong's (2018) submission that exporters had a positive behaviour towards CI practices but could not make good use of them due to a lack of knowledge and deficiencies in the organisation's technological and IT systems support.

Wright, Bisson and Duffy (2013) found substantial room for improvement across the diagnostic framework, including attitude, gathering, location, technology support, IT systems support, and, lastly, decision-makers use of intelligence-based output. New technologies could still positively affect CI performance and change how intelligence is gathered and disseminated through the organisation (Tahmasebifard & Wright, 2018).

However, this research result contrasts with Asghari et al. (2020), who found that information technology significantly and positively influenced CI. Similarly, Koriyow and Karugu (2018) found that CI assisted in monitoring technology, customer base, competitors, ecology, suppliers and economics. This result implies that an organisation's technology position may determine its competitive advantage and innovation opportunities, so the set of technologies the organisation has mastered informs innovation and CI (Sarica et al., 2019).

Tahmasebifard and Wright (2018) opined that technical information about competitors could impact a company's competitive advantage. Therefore, organisations that embrace technology achieve market share and satisfy the customers' needs (Asghari et al., 2020).

Peng (2021) likewise found that CI improves products, markets, and technological innovation. This finding demonstrates that new technical solutions provide organisations with a competitive edge by allowing them to lead in technology and provide distinctive goods, resulting in greater market performance (Hamel & Prahalad, 1994). This viewpoint is consistent with Lo et al. (2016), who found that technology and entrepreneurial approach were positively associated with a company's non-financial and financial success.

Also, the authors found that top management support was positively related to financial performance only. Additionally, Hussein et al. (2011) indicated that using CI led to innovation and ensured the organisation's survival. These findings show that technology adoption encourages communication, delivers customer service, and helps organisations maintain and improve their level of performance (Ozuem et al., 2019). If technology can be successfully deployed and used, it can produce many strategic and operational benefits for organisations.

However, adopting and deploying new technology in an organisation is more complicated than individual innovation decisions since more individuals participate in the decision-making process (Rogers, 2010). This view implies that top management plays an influential role in technology adoption. In this manner, top management can influence

technology adoption through their proactive innovativeness and interest in change (Piaralal et al., 2015).

Concurring, Hameed and Counsell (2012) found that the CEO's innovativeness and knowledge of the technology considerably influenced its adoption except for the manager's tenure. Also, research by Martin and Matlay (2003) and Mehrtens, Cragg and Mills (2001) identified the critical role of the CEO in influencing the adoption of new technology in small and medium-sized firms.

Gangwar et al. (2015), and Sila (2013) reported that top management support contributed significantly to technology adoption. In contrast, Duh and Fabiao (2018) found that top management support did not contribute significantly to mobile banking technology adoption. Moreover, some studies found no need for top management support to adopt technology (Gutierrez et al., 2015; Lian et al., 2014).

Given that technological superiority provides numerous opportunities for businesses to obtain data from internal and external sources, companies must invest in technology that gathers, saves, and analyses large amounts of data (Zhu et al., 2014).

Organisations cannot establish an accurate image of their technology position without technology intelligence since the quality information obtained on current and future technology trends significantly impacts the efficacy of technology management in organisations (Iansiti, 2000).

Consistently, Rudolph, Gilmont, Magee and Smith (1991) opined that many organisations had a real opportunity to benefit from CI since they struggle to realize the power of technology to reduce risk and identify opportunities in their businesses. Therefore, SA insurance companies must link technology intelligence to CI to sustain competitiveness. Combining customer value innovation with technological intelligence improves a company's chances of long-term profit and success (Koriyow & Karungu, 2018).

7.3.4.4 Information Providers

Customers are demanding more information; thus, information providers are reacting by making more information available online and in a searchable style, allowing information sources to be readily available to users of various networks (Kashyap & Sheth, 1994).

External information providers, on the other hand, are valued during the information collecting process since they control the quality of the data they supply (Markovich et al., 2019). The hypothesised path between information providers and CIE endorsed a positive and statistically significant relationship.

In this sense, H12 ($\beta = 0.158$, $T=2.171$, $p <0.050$, $f^2= 0.021$) stated that the organisation's enduring relationship with information providers is positively related to competitive intelligence embeddedness was supported. This finding aligns with Markovich et al. (2019), who found that information providers positively impacted CIE. In addition, Markovich et al. (2019) found that partnerships with information providers had a critical role in boosting the internal organisational characteristics that contributed to the CIE's development.

Equally, this finding correlated with Sarraf and Esfahani (2020a), whose study showed the positive impact of competitive intelligence web resources and alliance with information providers in competitive intelligence.

Notably, information providers provide accurate, relevant, and trustworthy information for leaders to make strategic decisions. As a result, the CIE's development in the organisation is aided by the strength of the relationship with information providers (Markovich et al., 2019, p. 710).

Hence, Markovich et al. (2019) discovered that CIE positively correlated with the strength of the organisation's relationships with information suppliers. The core responsibility of information providers is to provide answers to specific questions. In contrast, the role of CI is to interpret information and provide management with a perspective on risks and opportunities (Gilad, 2016). For that reason, Uzohue and Yaya (2016) determined that information specialists were still valuable for businesses.

Furthermore, they may utilise their CI abilities to develop a creative and unique technique of getting information from the internet, which they can use to promote their organisation's image and fulfil its stated aims. This result implies that information professionals give the organisation an edge by responding to crucial information with a feeling of urgency (Havenga & Botha, 2003).

As CI is crucial for organisations to stay abreast of the changing market condition and have a competitive edge, information professionals have experience dealing with database vendors. In this manner, they improve and advocate change in an organisation by employing a valuable strategy to provide intelligent decision-making information (Uzohue & Yaya, 2016).

This viewpoint demonstrates the importance of CI, which necessitates exceptional skills and understanding of internal and external intelligence sources for information workers (Oder, 2001). Meanwhile, Uzohue and Yaya (2016) opined that information professionals know where to source accurate information for decision-makers of an organisation due to their experience in dealing with database vendors. Furthermore, Uzohue and Yaya (2016) added that information professionals have adequate skills to search for specific information on databases that meets individuals' requirements.

CI approaches, therefore, enhance services rendered by information professionals in organisations. It helps them to realise new opportunities, which leads to innovation and, in turn, improves the organisation's and information professionals' position (Uzohue & Yaya, 2016). In recent research, Bao (2020) found that both opponent and supplier CI positively affected exploratory and exploitative service innovation. Furthermore, according to Bao's (2020) research, customer CI has a stronger impact on exploratory service innovation than exploitative service innovation.

Because CI involves gathering raw information and providing an enabling environment for decision-making, the internet helps collect data that improves customer services and business processes, bringing new products to the market and innovating new ideas (Uzohue & Yaya, 2016). For that reason, information professionals incorporate CI in their

daily routines to better manage information for competitive advantage in an organisation (Uzohue & Yaya, 2016).

Therefore, SA insurance companies should consider outsourcing part of their CI activities to the information providers to acquire knowledge on competitors, customers, and suppliers and provide leaders with helpful information for making strategic decisions.

Meanwhile, organisations have recognised that consumers and suppliers provide competitive information (Lee, Park, Yoon & Park, 2010). This view is consistent with Tanev and Bailetti's (2008) research, which found that specialised suppliers had the highest rate of sourcing competitive information. This finding validates the notion that internet-centred information providers are more progressive while traditional enterprise IT providers impede (Degerstedt, 2015b).

Similarly, Lemos and Porto (1998) discovered that professional supplier information was the most helpful in driving innovation and that customer information was the most significant to the innovation process. With the internet playing an essential role as a valuable source of information, web information has emerged as a vital source of CI for organisations (Tan, Foo & Hui, 2002).

This viewpoint attests that much of the information utilised by CI comes from specialists outside the company. It makes strategic decisions by combining secondary sources from outside the organisation with inside data (Calof, 2017b). In essence, CI interprets quality information sourced from web-based aggregators of information outsourced collectors for strategic decision-making (Gilad, 2016).

Consistent with this view, a study by Markovich et al. (2019) showed that CIE positively impacted web information quality and alliances with information providers. Since CI providers focus on organised CI, information providers should meet the needs of various information users in organisations and identify various strategies such as web mining to capture big data and online resources. In so doing, web mining can assist SA insurance companies in retrieving, processing and capturing information from web pages and documents on the Internet (Silva, Pacheco, Negrete, Niño, Lezama & Varela, 2019).

In addition, information professionals must have the foresight to determine the most relevant sources and convey this knowledge to organisations. In essence, information providers may aid organisations in turning data into insight by supporting them in managing their data (Diyaolu, 2019).

7.3.5 Employee Role Clarity

Employee work activities are guided and coordinated by role definition. In essence, role clarity ensures that employees know what they need to do and what is expected from them by setting task objectives in workgroups (Hassan, 2013). Role clarity also emphasises the alignment of employees and teams to their organisation's objectives (Kim, Kim & Kwon, 2020). The following subsections discuss the results of the hypothesised paths between employee role clarity, CIE, and organisational performance.

7.3.5.1 Employee Role Clarity and Competitive Intelligence Embeddedness

The degree to which an individual gets and comprehends information essential to accomplish their job is referred to as role clarity (Kundu, Kumar & Lata, 2021). Role clarity assesses whether workers clearly understand their work's goals and duties and the processes necessary to do the tasks assigned to them (Kim et al., 2020, p. 8). The hypothesised path between employee role clarity and CIE was insignificant. Therefore, H13 ($\beta = 0.115$, $T=1.578$, $p > 0.050$, $f^2= 0.013$), which states employee role clarity positively influences competitive intelligence embeddedness was not supported.

This research result is inconsistent with Du Plessis and Gulwa (2016), whose research showed that teams produced CI that focused on particular aspects of the competitive environment. Furthermore, Du Plessis and Gulwa (2016) indicated that employees were self-reliant in gathering CI for their organisation. Concurring, Dishman and Calof's (2008) study revealed that companies frequently obtain information about rivals or upcoming technologies from their employees.

Equally, Du Toit and Sewdass (2015) found that industry experts, direct consumer feedback, and employees are major sources of competitive information for SA businesses. Previous research by Calof (2017a) found that internet websites and

company employees were top secondary and primary sources of information, respectively.

Gračanin et al. (2015) likewise found that the internet and employees were proven to be CI primary information sources for all EU and Serbia companies. These findings show that employees may efficiently gather and use CI since they are closer to the source (Hughes et al., 2013). Muritala et al. (2019) found that CI has a favourable association with employee productivity, which supports this viewpoint.

This result indicates that employee cultural intelligence improves their organisation's productivity and collection of competitive information. Furthermore, Karimi and Eshaghi (2018) found that employees cultural intelligence significantly impacted the validity of competitive information and CI. Role clarification guides and coordinates employee work-related activities by setting task objectives for the team (Hassan, 2013).

Essentially, employees behave innovatively at work if they understand their roles. Therefore employees cannot execute their tasks effectively if their positions are unclear (Kundu et al., 2021). In addition, Samie, Riahi and Tabibi (2015) discovered a substantial and direct link between role clarity and staff efficiency. Since employees are the primary sources of CI in organisations, this study finds it challenging to inspire and include employees in CI activities in SA insurance businesses. As a result, SA insurance businesses should foster an environment where workers view their roles as more precise.

7.3.5.2 Employee Role Clarity and Organisational Performance

Role clarity is essential to employees as it determines how well tasks are performed and, consequently, an employee's performance (Mishra & Kumar, 2019, p. 2). Therefore, role clarity improves employees' job satisfaction and performance. Thus, a lack of role clarity results in employees assuming other responsibilities and ignoring what they are supposed to do (Nansubuga & Munene, 2013). The hypothesised path between employee role clarity and organisational performance showed that employee role clarity significantly affected organisational performance.

This finding supports H14 (β = 0.377, T=8.094, p<0.050, f^2= 0.305), which states that employee role clarity positively influences organisational performance. This finding is in line with Ahmed et al. (2017), who found a strong positive association between job discretion and company success in their study.

Equally, Azarpira, Yaghobi, Forghani and Soleimani (2013) found that employee role clarity increased the consistency and perception of their job performance. The result of this current study indicates that employees were clear about their job roles within the current organisational climate (Mishra & Kumar, 2019). Therefore, leaders should tailor a compelling vision for the organisation, establish well-defined responsibilities for employees, provide a team direction, and improve its capacity to thrive (Lynn & Kalay, 2015).

Consistently, Kim et al. (2020) found that strategy alignment was linked to organisational performance indirectly through goal clarity and employee engagement. In agreement, Samie et al. (2015) discovered statistical significance between role clarity, overall staff efficiency, and alignment with organisational goals. Furthermore, Lynn and Kalay (2015) found that vision clarity positively affected team performance. Their research, on the other hand, indicated that vision support and role clarity had little impact on team performance.

Therefore, these results authenticate that employees' high performance affects the team and the organisation (Purnama, 2013). Role clarity increases employee productivity and organisational performance and employees' efforts and engagements result in organisational productivity (Musgrove, Ellinger & Ellinger, 2014). Since conflicting goals impede employee productivity and performance, role clarity will improve employee job satisfaction and performance (Mishra & Kumar, 2019).

In a similar study, Thangavelu and Sudhahar (2017) discovered a substantial link between role clarity, performance feedback, and employee happiness regarding performance perception. Job satisfaction, commitment, employee behaviours, and organisational culture drive employees' and organisations' performance. This view aligns with Purnama's (2013) results which showed that organisational culture, job satisfaction, and commitment significantly impacted organisational citizenship behaviour.

Purnama's (2013) research also found that organisational commitment and citizenship behaviour substantially impacted organisational success. Organisational culture, work happiness, organisational commitment, and organisational citizenship behaviour all substantially impact organisational success.

Similarly, Rahimic (2013) found that organisational climate significantly correlated with performance, organisational effectiveness, productivity, commitment, anxiety and tendency of employees to leave. These results demonstrate that employee happiness has a long-term impact on an organisation’s capacity to attract and retain personnel and decrease turnover rates.

Consistently, Hassan (2013) found that offices with a high level of role definition had considerably greater levels of job satisfaction and reduced turnover rates. Furthermore, Hassan's (2013) research found that overall role clarity in these offices moderated the effects of role clarification on job satisfaction and turnover behaviour.

Cakmak, Öztekin and Karadağ (2015) also discovered that leadership and work satisfaction had a significant positive association. This result validates the importance of leadership support in motivating employees to carry out tasks and drive adequate performance in organisations (Kumar & Bhatti, 2020). Leaders play an essential role in helping employees accomplish their tasks and creating an atmosphere and a culture of enthusiasm and productivity (Alghazo & Al-Anazi, 2016).

For that reason, Osborne and Hammoud (2017) showed that the relationship between leaders and workers was essential for engaging employees and increasing organisational profitability. This finding aligns with Al Khajeh's (2018) submission that leaders help workers improve their relationships to achieve the organisation's common goals and objectives.

Role clarity, in essence, is a mediator between organisational socialisation strategies and self-rated task performance (Lapointe et al., 2014). Kauppila (2014) also found that employees with higher-quality connections with their leaders reported much greater job clarity. This finding is congruent with Newman et al. (2015b), who discovered that when

the positive association between ethical leadership and assisting behaviour was stronger, subordinates experienced higher degrees of role clarity. Furthermore, the authors found a stronger negative link between ethical leadership and deviant behaviour.

Similarly, Al Khajeh (2018) showed that autocratic, democratic, and transformational leadership styles positively correlated with organisational performance, while bureaucratic, charismatic, and transactional leadership styles were negatively associated with organisational performance. Admitting these results, Baig et al. (2021) found that transformational leadership significantly impacted employee performance.

In addition, Tanjung and Basri (2017) discovered that the structure of the initiative's leadership style had a beneficial impact on the clarity of purpose, implying that the higher the implementation of the initiative leadership style structure, the more clearly specified objectives. This finding shows that leadership style plays a significant role in clarifying organisational goals. Leaders that embrace participatory and transformational leadership are more likely to create a motivating environment among their workers.

Thus, SA insurance firms should implement leadership styles that develop people's capacities and abilities (Alghazo & Al-Anazi, 2016). In this manner, leaders of the SA insurance companies need to direct and motivate their employees to achieve organisational goals and improve organisational performance.

7.3.6 Competitive Intelligence Embeddedness and Customer Satisfaction

CIE transfers knowledge from external, competitive, and relevant information sources throughout the organisation to make strategic and technical decisions (Sarraf & Esfahani, 2020). Furthermore, Sarraf and Esfahani (2020) added that CI impacts the organisation's performance with the mediating role of customer satisfaction. Using the information gained from the knowledge of CI has therefore increased customer satisfaction and the organisation's financial performance. The hypothesised path between CIE and customer satisfaction showed a positive relationship and was robustly statistically significant. In this sense, supporting H15 ($\beta = 0.0711$, $T=15.953$, $p<0.050$, $f^2= 1.023$), which states that competitive intelligence embeddedness positively influences customer satisfaction.

This finding correlates with research studies by Markovich et al. (2019), and Sarraf and Esfahani (2020), which established that CI was essential in increasing customer satisfaction. Similarly, Al Dabbas and Alkshali's (2021) study showed a significant impact of CI intelligence on the contentment of customers.

This conclusion stems from the nature of CI that provides market information, indicating that CI is a capability that fosters a positive customer experience in every state of the customer journey (Hughes et al., 2013). Calof (2017a), and Calof et al. (2018) corroborated the above findings and found that CI was the most frequently used metric to measure customer satisfaction. Afolabi and Adegoke's (2014) study likewise concluded that customer satisfaction contributed to the organisation’s profit, achieved through CI.

Concurring, Markovich et al. (2019) discovered that CIE had a favourable impact on consumer satisfaction but had an interceding effect on performance. This finding aligns with the robust performance of previous research on CI orientation (Kumar et al., 2011).

In addition, this finding complements Markovich et al. (2019), which showed that CIE through customer satisfaction sequentially impacts performance. In contrast, Oyomo (2019) showed that customer life cycle and value had significant positive relationships. In contrast, customer experience showed a significant negative relationship to CI.

SA insurance companies should consider CIE-related aspects to improve customer satisfaction. They should also develop the integration and application of CI by combining the organisation's resources to create value for customers (Blenkhorn & Fleisher, 2001; Gračanin et al.,2015). In addition, SA insurance companies need to use the information gained from the knowledge of CI to enhance customer satisfaction.

7.3.7 Customer Satisfaction and Organisational Performance

Customer satisfaction plays a significant role in organisational performance. Furthermore, customer satisfaction provides management with insights to make informed decisions based on quality inferences from data mining (Afolabi & Adegoke, 2014). The hypothesised path between customer satisfaction and organisational performance was

statistically significant by endorsing H16 (β = 0.354, T=5.792, p<0.050, f^2= 0.198), which states that customer satisfaction positively influences organisational performance.

This finding correlates with Odunlami et al. (2013), who confirmed that customer satisfaction led to more profitability and found a positive correlation between customer satisfaction and organisational success. Moreover, Odunlami et al. (2013) concluded that customer satisfaction leads to more profitability. Consistently, Zakari and Ibrahim (2021) concluded that business success significantly impacted customer satisfaction.

In contrast, Neupane's (2014) research found a slight positive association between business performance and the contentment of customers. A recent analysis by Ndubisi and Nwankwo (2019) found significant positive relationships between customer satisfaction and bank performance across all factors investigated in a recent study.

Similarly, previous studies have revealed that the contentment of customers had an impact on several areas of financial success as well as the future performance of an organisation (Anderson et al., 2004; Banker & Masruwala, 2007, Ittner & Larcker,1998).

Customer satisfaction also affected several matrices of company success (Van Der Wiele et al., 2002). Budur and Poturak (2021) found that customers' perceptions of staff performance had a favourable and substantial influence on customer satisfaction and loyalty.

In contrast, Budur and Poturak (2021) found that overall employee performance did not show any effect. Customer happiness has a causal link with employee contentment, and an awareness of the workers' satisfaction role was critical in their research (Kurdi, Alshurideh & Alnaser, 2020). Furthermore, Ndubisi and Nwankwo's (2019) research concluded that bank employees' satisfaction and positive attitudes promoted stronger customer loyalty.

Likewise, El-Adly (2019) found that customer satisfaction directly affected customer loyalty. In addition, Curtis et al. (2011) found that increased customer satisfaction, repurchase rates, and the formation of loyalty positively influenced the performance of organisations and led to a competitive advantage.

This finding is consistent with Budur and Poturak's (2021) study, which found that customer perception of performance is a critical factor in an organisation's long-term effectiveness.

Therefore, leaders of SA insurance companies should ensure that employees build close relationships with their customers to enhance customer satisfaction in the long run. Also, leaders of SA insurance companies should continuously identify the knowledge customer's hierarchy of needs to improve organisational performance.

7.3.8 Competitive Intelligence Embeddedness and Organisational Performance

CIE capacity is the level to which CI pervades the whole organisation, allowing tactical choices to be made in light of all relevant external competitive information, which significantly impacts organisational performance (Markovich et al., 2019, p. 708).

Developing a CIE capability advances the implementation of the CI cycle through the organisation. It integrates information for the internal creation of knowledge to improve performance (Moustaghfir, 2009). The hypothesised path between CIE and organisational performance showed a strong statistical significance; thus supporting H17 ($\beta = 0.251$, $T=4.834$, $p<0.050$, $f^2= 0.0111$), which states that competitive intelligence embeddedness positively influences organisational performance.

Markovich et al. (2019) likewise found that CIE impacted the company's performance with the mediating role of customer satisfaction. With customer satisfaction directly related to revenue growth, a study by Markovich et al.(2019) indicated that CIE was an essential factor influencing consumer satisfaction and, consequently, the organisation's performance.

Uzoamaka et al. (2017a) also revealed that competitor intelligence significantly influenced market share. Furthermore, Uzoamaka et al. (2017a) found that customer intelligence significantly affected quality service delivery. In addition, Akram and Waheed (2012) identified a substantial and favourable association between CI and organisational performance. This research backs up a study by Sepahvand et al. (2016), which found that CI had a favourable and substantial impact on organisational performance.

Similarly, research by Yin (2018) showed that CI was positively related to organisational performance. A recent study by Asri and Mohsin (2020) concluded that a relationship between CI practices and organisational performance exists. Equally, Irenaus et al. (2021) research determined a positive association between CI and organisational performance.

Also, Rapp et al. (2015) found a support relationship between Individual CI use and performance. Shahbandi and Farrokhshad's (2019) research showed that CI positively affected organisational performance and strategic flexibility. Moreover, Shahbandi and Farrokhshad (2019) found that strategic flexibility positively impacted organisational performance, showing the mediating role that strategic flexibility and CI significantly correlated with organisational performance.

In addition, Adidam et al. (2012) found that Indian firms that exhibited higher levels of CI activities achieved better financial performance results in the market context. This result signifies that organisations performing CI activities have a greater chance of gaining a competitive advantage. Therefore, CI activities have an impact on the market performance of firms.

Equally, the findings by Tahmsebifard and Wright (2018) revealed the considerable and favourable benefits of CI deployment on company success in the marketplace. These findings show that organisational success is critical to a company’s survival (Singh, Darwish & Potonik, 2016, p. 214).

Given that CI scans the environment and obtains market information for organisations to improve their competitive position, business leaders should embed CI to identify market opportunities, giving them an edge over competitors (Muritala & Ajetunmobi, 2019).

As organisations rely on daily information from web sources, they should invest in a dedicated unit to collect and manage web information. Magasa et al. (2014), and Stefanikova et al. (2015) also found that the implementation and utilisation of CI enhance performance and affect an organisation's sustainable growth.

Therefore, leaders of SA insurance companies need to instil the fundamental values founded on understanding and responding to the needs of customers and the necessity to search constantly for new opportunities in the market (Irenaus et al., 2021).

7.4 Conclusion

This chapter discussed this study's empirical research results. It began by discussing the results obtained from this study's measurement items. The results of the descriptive statistics showed mean score values above the midpoint of 3.000 out of 5.000, thus suggesting that all the participants agreed with the statements posed from the related items.

In addition, this chapter discussed the PLS-SEM results obtained from testing this study's hypothesis. This study's hypothesis testing showed statistical significance to support eight hypotheses declared to be true. In contrast, the study showed statistical insignificance from nine hypothesised relationships; hence, not supported.

The discussions also considered how the findings obtained in this study relate to results and observations presented in the literature and scholarly articles. The next chapter discusses this study's practical and theoretical implications and makes recommendations and concluding remarks.

Chapter Eight: Conclusions and Recommendations

8.1 Introduction

The fundamental goal of this study is to see how competitive intelligence embeddedness affects organisational performance in South African life insurance businesses. The preceding chapters presented and discussed the results obtained from the data analyses.

This present concluding chapter commences by summarising the key research findings related to path coefficients and hypothesis testing. Conclusions are drawn based on fundamental research findings.

Additionally, recommendations are presented based on the significant findings and gaps identified during the analysis. In addition, recommendations are offered depending on the important results and gaps revealed throughout the research. The chapter discusses the study's theoretical and practical contributions. Before delivering the final concluding remarks, this study addresses and underlines the study's weaknesses as well as future research ideas.

8.2 Summary of the Research Findings

This section mainly summarises the research findings from path coefficients and hypothesis testing. Hussain et al. (2018) stress that when the beta coefficient (β) is more significant, it results in the strongest effect of an exogenous latent construct on the endogenous latent construct.

In Chapter 6, Table 6.14, 6.15 and Figure 6.2 showed that the CIE-related factor had the topmost path coefficient of β = 0.711 compared to other β values in the model, which showed a greater variance value high effect, thereby affecting customer satisfaction. In contrast, the employee-related factor had the least impact on CIE with β = -0.194.

As for hypothesis testing, the PLS-SEM results accepted eight out of the 17 hypothesised relationships, and nine were rejected. The following subsections summarise research findings from path coefficients and hypotheses.

8.2.1 Path Coefficients

A standardised path coefficient between -1.00 and +1.00 can be used to assess the statistical significance and strength of the causal routes (Hoe, 2008,p. 79). To be deemed useful for debate, standardised pathways should be at least 0.200 and ideally over 0.300 (Chin, 1998). As a result, only the relevant route coefficients are discussed in this section.

The final PLS-SEM results revealed that the CIE factor had the highest path coefficient (β = 0.711), showing the strongest impact on customer satisfaction. This result suggests that SA insurance companies should pay more attention to CIE-related factors to improve customer satisfaction. In doing so, they should develop the integration and application of CI by combining the organisation's resources to create value for customers (Blenkhorn & Fleisher, 2001; Gračanin et al.,2015).

Among the three influencing path coefficients that impact organisational performance, employee role clarity (β = 0.377) directly affected organisational performance. This result is consistent with Ahmed et al. (2017), whose study concluded a significant positive relationship between work discretion and business performance. Similarly, Thangavelu and Sudhahar (2017) discovered a correlation between role clarity, performance feedback, and employee satisfaction regarding performance perception. This result implies that role clarity improves employee commitment and productivity.

Therefore, committed employees develop bonds with their organisations, creating organisational performance (Andrew, 2017). Also, improved employee productivity positively affects organisational financial performance (Osborne & Hammoud).

Furthermore, the path coefficients for customer satisfaction (β=0.354) and CIE (β=0.251) had a moderate indirect impact on organisational performance compared to employee role clarity. The path coefficient for customer satisfaction (β=0.354) indicates that customer service is critical for organisational performance. This result correlates with Odunlami et al. (2013), who confirmed that customer satisfaction led to more profitability and found a positive relationship between customer satisfaction and organisational profitability.

Ndubisi and Nwankwo (2019) revealed significant positive associations between customer satisfaction and bank performance among all the tested variables. This result shows that SA insurance companies' employees enhance customer satisfaction by building close relationships with their customers in the long run. Furthermore, this result indicates that employees are aware of increased customer knowledge and hierarchy of needs, improving customer satisfaction and organisational performance.

Additionally, the PLS-SEM results showed that the information usefulness-related factor had the highest path coefficient (β 0.325) compared to strategy (β 0.203), information providers (β 0.158), and employees (β -0.194), with the overall affecting CIE. Among these five essential CIE influencing path coefficients, the information usefulness related path coefficient (β 0.325) significantly affected CIE. This result corresponds with Itani et al. (2017), who found a positive relationship between social media use and CI collection.

Aramide and Adebisi (2018) established a connection between CI with information in an organisation. This result demonstrates that SA insurance companies allocate enough internal organisational resources. Moreover, this result suggests that SA insurance companies subcontract with external consultants to provide them with compact and analysed relevant information to improve CI use across the organisation and CI practices (Markovich et al., 2019).

The path strategy (β 0.203) showed that strategy significantly impacted CIE. This finding supports Maritz and Du Toit's (2018) finding, whereby they demonstrated that strategy and CI were inseparable. Cavallo et al. (2020), who established empirical evidence on the connection and usage of CI practices throughout each step of the strategy creation process, agree with this conclusion. This result implies that SA insurance companies have strategies that focus on micro-organisational practices.

Furthermore, these results show that these insurance companies' organised intelligence functions create synergies between CI and the organisation's strategy. Moreover, the Information provider's path coefficient (β 0.158) significantly impacted CIE. This result concurs with Sarraf and Esfahani (2020), whose study showed the positive impact of CI web resources and alliance with information providers in competitive intelligence.

Markovich et al. (2019) also found that information providers positively impacted CIE. This result validates that information providers provide accurate, relevant, and trustworthy information for strategic decisions.

The path coefficient employees (β -0.194) also showed the slightest significant impact on CIE. This result is congruent with the findings from Calof (2017a), Calof et al. (2018), and Calof and Sewdass (2020), which reported that most employees knew that CI existed, and on average, some took part in CI activities.

This result indicates that employees are actively involved in CI activities and that CI is available for use by many employees in organisations (Marin & Poulter, 2004). Equally, this result demonstrates that SA insurance companies practice a culture that encourages employees to share knowledge among themselves.

8.2.2 Hypothesis Testing

This study's integrated conceptual model comprises seventeen hypotheses. This section provides the research findings from this study's seventeen hypothetical relationships.

8.2.2.1 Organisational Factors

The employee, leadership, strategy, structure, and process are organisational factors predicted to influence CIE. The hypothesised path between strategy and CIE showed that strategy significantly impacted CIE. As a result, H1 (β = 0.203, T=2.231, p <0.050, f^2= 0.048) was supported. This finding corroborates Maritz and Du Toit (2018), who found that strategy and CI were inseparable.

Concurring, Cavallo et al. (2020) showed empirical evidence on the linkage and use of CI practices at each stage of the strategy development process. This result denotes that SA insurance companies have a CI-specific function that monitors and evaluates business strategies so that leaders can use those insights to take corrective action and respond swiftly to the competition (Maritz & Du Toit, 2018). CI also permits organisations to adopt different strategies to achieve a competitive advantage and become market leaders (Acar, Zehir, Özgenel & Özşahin, 2013).

The hypothesised path between employees' capabilities and CIE also showed statistical significance, thereby endorsing H4 (β = -0.194, T=2.631, p <0.050, f^2= 0.030). This result is consistent with Cekuls's (2015a) findings that employees regularly provided their superiors with information on the competitive environment.

Similarly, Wright and Calof (2006) reported a high percentage of company employees being aware of and involved in CI activities suggesting that most employees knew that CI existed and thereby took part in CI activities (Calof (2017; Calof et al.,2018; Calof & Sewdass, 2020). In essence, this result highlights that employees of the SA insurance companies are capable and motivated to gather intelligent information for their respective organisations.

In contrast, the hypothesised path between leadership and CIE showed that leadership and CIE were statistically insignificant, rejecting H2 (β = -0.081, T=1.092, p >0.050, f^2= 0.006). This finding is inconsistent with De Almeida et al. (2016), who showed that top management support for the CI processes correlated positively with a tracker's intrinsic motivation. However, Duh and Fabiao (2018) found that top management support impacted mobile banking adoption insignificantly.

This finding shows the absence of culture amongst the leadership of the SA insurance companies to embrace CI practices and drive knowledge sharing throughout the organisations. This result further suggests a lack of leadership commitment and support for CIE activities and shows no pressure to entrench CI practices within their organisations. In addition, the hypothesised path between structure and process and CIE showed statistical insignificance, thereby rejecting H3 (β = 0.118, T=1.273, p <0.050, f^2= 0.008). This result is consistent with Viviers et al. (2002), who found that SA businesses lacked the necessary tools to undertake effective intelligence operations, particularly regarding method and organisation, analysis, and awareness.

Dishman and Calof (2008) found that the CI practices effectively collected information but were ineffective when processing capability and performing analysis. Similarly, Nasri's (2011) research revealed that businesses were underinvesting in the internal

infrastructure needed for effective intelligence efficacy. This result implies that SA insurance companies somewhat do not have adequate structures that support CI

8.2.2.2 Information Attributes

Information accuracy, credibility, quality, and usefulness are among the information attributes impacting CIE. The hypothesised path between information quality and CIE showed statistical insignificance. In this sense, H5 (β = 0.028, T=0.296, p >0.050, f^2= 0.000) was not supported. This result is inconsistent with Markovich et al. (2019), who found that web information quality resources correlated with CIE.

Ho (2008) likewise found that the perceived quality of web competitive information sources and management's action-orientated use of that information impacted the organisation's CIE capabilities and performance. This result suggests that SA insurance companies are not allocating enough resources to a dedicated CI function conducting systematic competitive information reviews.

Additionally, the hypothesised path between information credibility and CIE showed statistical insignificance. As a result, H6 (β = 0.183, T=1.899, p >0.050, f^2= 0.017) was not supported. This result suggests that SA insurance companies cannot source credible information during the collection phase. Maungwa and Fourie (2018a) also found a lack of conceptual understanding underlying CI processes and the articulation and expression of intelligence needs within CI activities attributed to CI failures.

Equally, the hypothesised path between information credibility and CIE showed statistical insignificance. Meanwhile, H7 (β = -0.071, T=0.688, p >0.050, f^2= 0.003) was not supported. This result is congruent with Markovich et al. (2019), who found that information accuracy had no statistically significant relation with competitive intelligence embeddedness. This result also highlights the need for employees to filter information to prevent inaccurate information from flowing through the organisation.

In contrast, the hypothesised path between information usefulness and CIE endorsed statistical significance between information usefulness and CIE, thus supporting H8 (β = 0.325, T=3.754, p <0.050, f^2= 0.064).

This result aligns with Itani et al. (2017), whose research found a positive relationship between social media use and CI collection. Similarly, Aramide and Adebisi (2018) established a connection between CI with information in an organisation.

These results suggest that CI gathers intelligence information used by leaders of SA insurance companies to achieve long-term strategic goals. The successful adoption of these strategic tools enhances organisational outcomes, including performance (Al-Ansaari, Bederr & Chen, 2015; Pinho, Rodrigues, Dibb, 2014).

8.2.2.3 Market Factors

The market factors impacting CIE include competition, customer insights, technology, and information providers. The hypothesised path between competition and CIE showed statistical insignificance. Consequently, H9 (β = 0.082, T=1.126, p > 0.050, f^2= 0.005) was not supported. This research result contrasts Asghari et al. (2020), whose study found that competitor information positively and significantly influenced CI.

Koriyow and Karugu (2018) likewise found that CI was crucial in analysing competition, evaluating the external environment, recognising political and regulatory difficulties, determining economic trends, and evaluating new technological developments. This result indicates that SA insurance companies are not using CI to stay ahead of the competition. Possibly, SA insurance companies use CI to keep abreast with new and pending legislative trends liable to impact them (Du Toit & Sewdass, 2015; Pellissier & Kruger, 2011; Sewdass & Du Toit, 2014).

Furthermore, the hypothesised path between customer insights and CIE showed statistical insignificance and did not endorse H10 (β = 0.111, T=1.538, p >0.050, f^2= 0.010). This result contrasts Du Toit and Sewdass' (2014a) study, revealing that organisations used CI to gather competitive information and customer feedback.

Congruently, Oyomo (2019) showed that According to the Entropy technique, customer-centricity and its dimensions considerably impact competitive intelligence, with customer life being the most important. Moreover, Amarouche et al. (2015) found the importance of CI among the data analysed from customer opinions.

Similarly, Pellissier and Kruger (2011) showed that prominent organisations used CI for strategic decisions and insights into customer analytics and markets. This result advocates that SA insurance companies struggle to unlock large volumes of raw data into actionable customer insights. Furthermore, they are not using CI to perform predictive analytics to interpret events past customer life cycles (Kwach, 2018).

Meanwhile, this result implies that SA insurance companies experience challenges using published and non-published sources. Moreover, they are likely unable to solve complex problems, react quickly to the customer life cycle, and drive efficiencies (Oyomo, 2019).

In addition, the hypothesised path between technology and CIE showed statistical insignificance. As a result, H11 (β = -0.099, T=1.169, p >0.050, f^2= 0.009 was not supported. This finding aligns with Bisson and Tang Tong (2018), whose study showed that exporters had a positive behaviour towards CI practices but could not make good use of them due to a lack of knowledge and deficiencies in the organisation's technological and IT systems support.

Wright, Bisson and Duffy (2013) also showed that all strands of the diagnostic framework indicated substantial room for improvement: attitude, gathering, location, technology support, IT systems support, and ultimately, decision-makers utilisation of intelligence-based output.

In contrast, Asghari et al. (2020) found that information technology significantly and positively influenced CI. Koriyow and Karugu (2018) found that technology, client base, rivals, ecology, suppliers, and economics were all monitored using CI. Rudolph et al. (1991) also suggested in their research that many companies had a real opportunity to benefit from reduced risk and enhanced opportunities due to CI since they strive to realise the power of technology in their businesses.

This result implies that SA insurance companies do not have adequate IT capabilities and infrastructure that effectively support CI. Furthermore, these results demonstrate that SA insurance companies might not choose the appropriate technologies that support their CI activities.

On the contrary, the hypothesised path between information providers and CIE endorsed a positive relationship and was statistically significant, therefore supporting H12 (β = 0.158, T=2.171, p <0.050, f^2= 0.021). Corroborating this result, Markovich et al. (2019) found that information providers positively impacted CIE. Markovich et al. (2019) further revealed in their study that partnerships with information providers had a critical role in boosting the internal organisational characteristics that contributed to the CIE's creation.

Equally, this finding is consistent with Sarraf and Esfahani (2020a), whose study showed the positive impact of CI web resources and alliance with information providers in competitive intelligence. This result implies that SA insurance companies outsource some of their information activities to professional providers who promptly provide critical, relevant, and trustworthy information for strategic decision-making.

8.2.2.4 Employee Role Clarity

This section summarises the employee role clarity dimensions that have a bearing on CIE and organisational performance. The hypothesised path between employee role clarity and CIE was insignificant. Consequently, H13 (β = 0.115, T=1.578, p > 0.050, f^2= 0.013) was not supported. This research result is inconsistent with Du Plessis and Gulwa (2016), whose research showed that teams produced CI focusing on specific elements of the competitive environment. Furthermore, Du Plessis and Gulwa (2016) indicated that employees were self-reliant in gathering CI for their organisation.

Dishman and Calof's (2008) study also revealed that employees frequently provided information about rivals or upcoming technology to employers. This contrary result highlights the absence of role clarity creating unnecessary confusion in employees' minds regarding their roles in sourcing CI for the SA insurance companies.

Consequently, employees of SA insurance companies seem to do their job tasks with the least involvement, apart from the workplace being an essential factor that directly impacts employees' efficiencies. This view concurs with Walia and Narang's (2015) finding that job participation is adversely connected with role ambiguity. This result affirms that

dedicated and meaningful work enables employees to realise their value and engages them (Osborne & Hammoud, 2017).

Conversely, the hypothesised path between employee role clarity and organisational performance showed that employee role clarity significantly affected organisational performance, thus supporting H14 (β = 0.377, T=8.094, p<0.050, f^2= 0.305). This result concurs with Ahmed et al. (2017), who concluded a significant positive relationship between work discretion and business performance.

Azarpira et al. (2013) likewise found that employee role clarity of employees increased the consistency and perception of their job performance. This result shows that committed employees develop bonds that stimulate organisational performance (Andrew, 2017).

Furthermore, this result demonstrates that the commitment of employees resulting from role clarity is a consequence of the internal environment provided by the SA insurance companies that permit employees to achieve the organisational goals and enhance the organisation's performance.

8.2.2.5 Competitive Intelligence Embeddedness

This section summarises the competitive intelligence embeddedness dimensions that impact customer satisfaction and organisational performance. The hypothesised path between CIE and customer satisfaction showed a positive, robustly statistically significant relationship, thereby supporting H15 (β = 0.0711, T=15.953, p<0.050, f^2= 1.023). This finding correlates with research studies by Markovich et al. (2019), and Sarraf and Esfahani (2020), which found a positive effect on CIE and customer satisfaction.

Similarly, Al Dabbas and Alkshali's (2021) study showed a significant impact of CI intelligence on customer satisfaction. Afolabi and Adegoke (2014) concluded that customer satisfaction significantly contributed to the organisation's profit, achieved through CI. Oyomo (2019) showed that customer life cycle and value had significant positive relationships. In contrast, customer experience showed a significant negative relationship to CI. This result suggests that SA insurance companies leverage CI to pay attention to customer-focused intelligence.

Furthermore, they use CI to connect emotionally and create value for their customers. Instead of sticking to their conventional products and services, they seem to respond and offer solutions desired by their customers.

In addition, the hypothesised path between CIE and organisational performance showed a strong statistical significance. As a result, H17 (β = 0.251, T=4.834, p<0.050, f^2= 0.0111) was supported. Markovich et al. (2019) consistently found that CIE impacted the company's performance with the mediating role of customer satisfaction. Moreover, Markovich et al.(2019) showed that CIE is an essential factor influencing consumer satisfaction and performance.

Equally, Irenaus et al. (2021) also showed a positive relationship between CI and organisational performance. Concurring, Yin (2018) showed that CI positively correlated to organisational performance. In tandem, Sepahvand et al. (2016) found a positive and significant effect of CI on organisational performance.

Asri and Mohsin (2020) also concluded a relationship between CI practices and organisational performance. This finding shows that SA insurance companies might be using information gained from the knowledge of CI to increase customer satisfaction and the company's performance.

Therefore, this result implies that SA insurance companies utilise CI to gather accurate and relevant information on their internal and external business environment and develop strategies that enhance their market share and organisational performance.

8.2.2.6 Customer Satisfaction and Organisational Performance

This section summarises customer satisfaction dimensions that impact organisational performance. The hypothesised path between customer satisfaction and organisational performance was statistically significant, thus endorsing H16 (β = 0.354, T=5.792, p<0.050, f^2= 0.198). This finding conforms with Odunlami et al. (2013), who confirmed that customer satisfaction led to more profitability and found a positive relationship between customer satisfaction and organisational profitability.

Likewise, Odunlami et al. (2013) concluded that customer satisfaction led to more profitability. In conformity, Ndubisi and Nwankwo (2019) revealed significant positive associations between customer satisfaction and bank performance among all the tested variables.

Similarly, Curtis et al. (2011) found that increased customer satisfaction, repurchase rates, and the formation of loyalty positively influenced the performance of organisations and led to a competitive advantage. Zakari and Ibrahim (2021) relatedly concluded that customer satisfaction in business was positively affected by business performance.

In contrast, Neupane's (2014) research showed a weak positive relationship between customer satisfaction and business performance. This research results signify that SA insurance companies are aware of the contribution and value customers create for their businesses in improving their commercial performance.

This result infers that SA insurance companies use customer insights to build intimate relationships with customers to develop value-added products and services and sustain organisational performance.

8.3 Conclusion of Findings

The preceding section discussed a summary of the empirical results of the path coefficients and 17 hypotheses. This research aimed to investigate the effect of competitive intelligence embeddedness on organisational performance in SA life assurance companies. This study came to the following conclusions based on the quantitative analysis and summary of findings described in the previous section.

- The SA insurance companies lack leadership commitment, support, and a culture. The organisational culture yet encourages the use of intelligence and ensures the success and implementation of CIE.
- The SA insurance companies lack an organisational culture of mutual trust between leaders and employees, ensuring successful CI management across the organisation.

- The SA insurance companies lack adequate structures and processes that effectively support CIE. Furthermore, SA insurance companies are not leveraging technology to assist their CI functions in amplifying their business processes.
- The SA insurance companies rely on their employees and a network of peers to source CI information. However, employees who gather this intelligence must share their knowledge with colleagues to increase organisational innovation.
- The SA insurance companies do not have CI-specific functions or analytical capabilities to translate information into unique know-how. Data is not filtered during acquisition to prevent the inaccurate flow of information across the organisation. However, the SA insurance companies seem to use intelligent information to anticipate competitor actions and respond to offer solutions desired by their customers.
- The SA insurance companies are ineffective in identifying and responding to the operational environment's challenges, opportunities, and risks. Furthermore, SA insurance companies are not effectively using CI to gain a competitive advantage.
- The SA insurance companies seem to focus more on competitor intelligence rather than customer intelligence. Furthermore, they are not engaging with their customers to add, create, and unlock more value in response to their dynamics and demands.
- The SA insurance companies are lacking behind in technology positions. It seems as if SA insurance companies are not investing in new technologies that support CI to perform predictive analytics and unlock large volumes of raw data into actionable insights. Additionally, top management seems not to influence technology adoption, which can be attributed to their inability to innovate, and lack of knowledge of the technology.
- The SA insurance companies have partnered with information providers to acquire knowledge of competitors, customers, and suppliers and provide leaders with helpful information for making strategic decisions. In addition, information providers seem to provide the SA insurance companies with accurate and timely information about customers and the industry environment.

- The SA insurance companies rely on teams of varying sizes to source CI, creating role ambiguity and conflict among the employees. Furthermore, SA insurance companies struggle to manage information since various employees seem to collect CI on behalf of the organisations, leading to duplicating efforts impacting the accuracy and relevance of information.
- While there seems to be no employee role clarity for the SA insurance companies, they have created a meaningful work environment that enables employees to be fully engaged, increasing their productivity and organisational performance.
- Moreover, SA insurance companies' leadership played a significant role in helping employees realise their ambitions by creating an atmosphere and a culture of enthusiasm and productivity.
- The employee satisfaction and positive attitudes of SA insurance have promoted customer loyalty and satisfaction. Furthermore, SA insurance companies seem to embed CI to add value to their customers by offering products and services that meet their differentiated needs.
- The SA insurance companies have somewhat implemented drivers that monitor CI and increase customer satisfaction and financial performance.

Based on the above, this research concludes that the SA insurance companies apply CI with relative success in some areas of their operation, but more formalised processes and structures will benefit the insurance industry. The SA insurance industry faces obstacles directly related to employees, including people, leadership, process, structure, and technology.

In addition, there seems to be an element of negative attitudes from the perspective of management and employees, resulting in inadequate management support for embedding CI throughout the organisation’s value chain. The corporate culture is not conducive to CI, thus resulting in a lack of accuracy, quality, and relevance of intelligence despite management and employees using CI to transfer knowledge across the organisation. However, the SA insurance companies should develop a CI capability and consider practical solutions to ensure its success irrespective of these challenges.

8.4 Recommendations

The recommendations for this study are discussed in detail below.

8.4.1 Strategy

Organisations adopt strategic management processes, including formulating, implementing, and evaluating the strategic actions to achieve long-term organisational goals (Ahmed et al., 2018). CI thus adds value to planning and the organisation's decision-making processes. The linkage between CI intelligence and strategic management is critical (Bulley et al., 2014, p.83); hence, this study found a synergy between strategy and CIE.

With strategy assisting organisations in setting goals and providing direction, organisations need knowledge-related functions and CI to support the strategy's formulation, application and assessment (Asghari et al., 2020).

SA insurance companies should therefore develop a CI function with a strategic focus and allocate enough resources to operate this specific function. Furthermore, SA insurance companies should invest in a CI-specific function that will contribute to the tactical formulation of strategy and focus mainly on strategy execution and monitoring so that executives may make educated decisions based on input about the plan's performance in the market (Cavallo et al., 2020).

This recommendation demonstrates that the organisation's strategy pays more attention to micro-organisational practices. In tandem, CI monitors and evaluates the organisation's strategy and provides leaders with insights to take corrective action and respond swiftly to the competition (Maritz & Du Toit, 2018).

The CI-specific function will therefore ensure that strategic practices are employed and allocate resources appropriately to steer the company in the right direction and set in processes to monitor and control the organisation's strategic outcomes (Jarzabkowski, 2003).

Moreover, the CI function will integrate strategic processes and practices within different levels in the organisation, thereby facilitating the inclusion of all managers in strategy to ensure rapid implementation of strategic decisions (Davis et al., 2016; Jansen Van Rensburg et al., 2014).

8.4.2 Leadership

As the COVID-19 pandemic continues to disrupt businesses and markets, organisations continue to reinvent themselves, recognising the importance of CI irrespective of their size. As organisations face volatility, uncertainty, complexity and ambiguity, leadership is critical in shaping organisational strategies and preparing organisations to use technology to adapt quickly to the rapid changes (Schoemaker, Heaton & Teece, 2018).

This study showed a lack of leadership commitment and support for CIE leading to no pressure to entrench CI and highlighting that leaders of the SA insurance are not focusing and investing in CI activities. This finding validates that leaders sometimes fail to embrace CI and do not link this subject area to strategic planning (Köseoglu et al., 2016).

Importantly, leaders need CI to acquire knowledge about the environment, competitors, customers, development capacity and resources. Therefore, the top leadership of the SA insurance companies should take advantage of the current information climate by embedding CI values that encourage collaboration and information sharing among the employees.

Since leaders are responsible for the current organisational culture, they are also accountable for creating a new culture. Leaders of SA insurance companies should establish a CI culture in their respective organisations to ensure the success of CI efforts and CI's significant contribution throughout the organisation.

Furthermore, the top leadership of the SA insurance companies need to accept and be aware of the benefits created by CI. This recommendation concurs with Wright et al. (2008b), who advocated that leadership attention and awareness were vital in embedding CI throughout the organisation.

Additionally, leaders of SA insurance companies should strive to enhance a CI culture by integrating CI throughout the organisation, embedded and aligned with the organisation's infrastructure (Viviers et al., 2005). Equally, leaders of the SA insurance companies should embrace values that foster a corporate culture that embeds CI activities to support and use them throughout the organisation.

In line with this recommendation, Saayman et al. (2008) pointed out that the share of CI in organisations is influenced by decision makers' awareness and acceptance of CI and a competitive culture such as employee engagement and management support that creates legitimacy and importance.

Concurring, Cekuls (2015b) showed that CI gathering strongly depended on the cultural values and the current organisational culture. Furthermore, Cekuls (2015b) concluded that leadership principles, trust, open communication, and cooperation all played a part in establishing the organisational culture and applying CI management throughout the company.

Top leaders of SA insurance companies should therefore create a corporate culture of mutual trust between themselves and employees to ensure the implementation and success of CI management throughout their organisations. In so doing, top leaders of SA insurance companies must share the organisation's vision and mission with their employees and create a conducive CI culture for employee involvement by providing adequate resources for embedding CI throughout the organisation.

In addition, top leaders of SA insurance companies should support and develop a culture of competitiveness and involve employees in the CI process. This recommendation is congruent with Opait et al. (2016), who suggested that leaders use trends and competitor analysis to involve CI personnel, staff, and supervisors to identify an organisation's competitiveness.

Equally, buy-in and support from senior management and employees of SA insurance companies are vital for the success of the CI processes within the organisations (Nasri, 2011). Concurring, Lackman et al. (2000) showed that the CI function seemed more

effective when a company emphasised active participation among all personnel in the CI process.

Therefore, leadership engagement authenticates the importance and implementation of CI processes together with a supportive organisational culture and contributes to the successful utilisation of CI throughout the organisation (Ardito & Petruzzelli, 2017).

Directors of the SA insurance companies must ensure that CI ownership resides at the organisations' top management structures. Leadership commitment from the board of directors and senior managers is needed to embed processes and procedures that support CI activities and enhance CIE capabilities across the organisation (Markovich et al., 2019).

8.4.3 Structure and Process

Due to the increasing complexity and dynamics of the complex business environment, structure and operating processes are central to the functioning of an organisation. However, organisations experience challenges in creating formal structures and processes that permit them to execute CI effectively (Frost, 2014).

The study found a lack of adequate structures and processes that supported CIE in SA insurance companies. Considering that CI processes depend on gathering people and resources from a range of internal units, leaders of SA insurance companies should encourage employees to contribute and participate in the CI activities within the organisation. Constraints attributed to resource allocation also pose a challenge for organisations.

Congruently, Ncube and Ndlovu (2015) found that companies encountered major challenges in implementing and practising CI due to a lack of financial resources allocated to CI activities and knowledge to execute CI operations.

As a result, executives of SA insurance firms must focus their efforts on planning, searching, analysing, and using relevant data from their surroundings to gain a competitive edge (de las Heras-Rosas and Herrera, 2021).

Nasri (2011) likewise suggested that Companies' CI activities and processes are influenced, encouraged, and developed by management support, culture, and structure. As the SA insurance sector is experiencing significant challenges and disruptions due to the COVID-19 pandemic, a culture of CI is thus necessary to gain advantage and growth.

Inevitably, leaders of SA insurance companies need to embed CI in company culture to inform innovation and strategic business decisions (Prinsloo, 2016). This recommendation concurs with Cekuls (2015b), who found significant correlations between organisational culture and CI.

Furthermore, leaders of the SA insurance companies should plan, support and implement CI processes in their organisations. They should create a culture that encourages the development of CI activities within the SA insurance sector. In this manner, leaders should foster an organisational culture that embeds CI activities to ensure that they are supported and used throughout the organisation (Saayman et al., 2008).

Since the findings highlighted the disconnectedness of the CI function, leaders of the SA insurance companies should create formal processes and structures and establish centralised operations for virtual teams to execute CI effectively and ensure that knowledge and information sharing flows across the organisation.

To address challenges directly connected to workers, such as people, management, expertise, and structure, SA insurance firms should adopt official rather than informal CI functions (Prinsloo, 2016). Essentially, the top leadership of the SA insurance companies should consolidate and make the most of and CI function so that it is used continuously in strategic decision-making.

Additionally, SA insurance companies should consider organisational structural changes and centralise the information sourcing activities within the CI function. In so doing, they need to create formal structures and processes that support CI through a specific function (Crayon, 2019; Calof, 2014; Reinmoeler & Ansari, 2016). The CI function will be an integrator between the senior and executive management and the employees.

Furthermore, the CI intelligence function will help anticipate and provide insights about market developments more rapidly than the competition. It will also fast-track management decisions and strategic actions (Arcos, 2016).

8.4.4 Employee Capability

In the turbulent business environment, organisations should proactively create, develop, and maintain employee capabilities to be more receptive to environmental change (Maley, 2019). This study indicated that employees used CI to source intelligent information for strategic decision-making.

This finding validates that the organisation's culture and the employees' understanding of collecting and exchanging business information play a fundamental role in accomplishing CI and disseminating information. Cekuls (2015b) revealed that the cultural values and present organisational culture are strongly associated with successful CI sourcing.

Furthermore, Cekuls' (2015a) study showed significant correlations between organisational culture and CI. Therefore, the top management of the SA insurance companies should promote a culture that supports social interaction to encourage employees to share knowledge within the organisation and improve the flow of information among the employees.

Concurring, Cekuls (2015a) found that trust was essential in enabling interactions within relationships and social exchanges. Cekuls (2015b) also revealed that mutual distrust did not facilitate a successful turnover of information among employees.

As a result, executives of SA insurance businesses should encourage their followers to embrace the shift based on the mutual trust they have built with their employees to build a knowledge-sharing culture. Employees will be encouraged to communicate knowledge among themselves in this manner. Since employees are the most critical primary intelligence source, SA insurance companies must provide the appropriate infrastructure to support information acquisition.

Congruently, Ezenwa et al. (2018) recommended that organisations invest adequately in CI processes, facilities, and activities to enhance product innovation, services and competitive dispositions. SA insurance companies should therefore integrate all employees into their intelligence efforts to improve the performance of the CI throughout the organisation (Calof, Richards & Santilli, 2017).

Given that top management always needs credible data to predict the future when making strategic decisions, leaders of SA insurance companies must ensure that employees' capabilities, such as technical skills and knowledge, are addressed to avoid delays in adopting CI practices. Moreover, leaders of the SA insurance companies should strive for communication, analysis, networking, collecting, planning, marketing, research, and strategic direction are all CI skills.

Consistent with this recommendation, Heppes and Du Toit (2009) pointed out that organisations should recruit employees with intellectual skills to operate their CI practices efficiently. SA insurance companies need CI that includes critical thinking, reasoning, idea development, and problem-solving. Similarly, Strauss and Du Toit (2010a) revealed that networking, analytical, and research skills were the three most important CI skills in SA.

Another research by Mabe et al. (2019) also found that leadership, management, strategic thinking, communication, and data analysis were classified as critical thinking, marketing, and research skills. These skills will ensure that SA life insurance companies' employees provide continuous, systematic calculations of the external environment, identify the opportunities, threats, and developments that might positively or negatively impact organisations, and positively influence proactive decision-making procedures (Du Toit, 2007, p.34).

Equally important, SA insurance companies require communication capabilities to foster effective and efficient communication in the workplace. Because CI practitioners may communicate relevant information to colleagues and the CI environment, communication skills are vital (Kurtz, Silverman, Draper, van Dalen & Platt, 2017). Meanwhile, employees of SA insurance companies in a CI environment need to have the ability to convey and

present information discovered from the external environment in a way that leaders of an organisation may use strategically (Strauss & Du Toit,2010a).

In addition, leaders of the SA insurance companies should establish communication capabilities that promote effective and efficient communication in the workplace. In that way, employees are empowered to use communication capabilities to communicate and present information from the external environment to be utilised strategically by organisational leaders (Strauss & Du Toit, 2010b). Communication capabilities are essential because CI practitioners can communicate relevant information to colleagues and the CI dedicated function (Mabe et al., 2019).

Similarly, De Almeida et al. (2016) supported this recommendation by showing that information technology positively correlated with tracker motivation. Conversely, research results by Cekuls (2015b) pointed out the problems in the communication system of companies to apply successful CI management. Furthermore, Cekuls (2015b) reported that respondents acknowledged that their companies have not set up a method for workers to submit their observations and contribute information, indicating the need to strengthen organisational communication.

8.4.5 Information Quality

Nowadays, organisations are daily relying on information retrieved from web information resources. Quality information, however, augments CI and impacts its implementation (Sarraf & Esfahani, 2020). Quality is therefore vital in distinguishing between usable and additional information.

To ensure that information quality exceeds customer satisfaction, organisations develop their analytical capabilities by maintaining an internal unit dedicated to analysing, collecting and disseminating web information (Markovich et al., 2019). This study showed that SA insurance companies did not have adequate screening processes that prevent information overflow from impacting CI to disseminate the quality of intelligence across the organisations. This study highlighted a lack of analytical capabilities that translate

information into unique know-how, suggesting that CI staff could not judge for misinformation.

Information quality is a key success element for CI, and it must be reviewed and analysed before being collected. SA insurance companies must develop screening procedures to improve the quality of intelligence sourced in the market (Sarraf & Esfahani, 2020).

SA insurance companies should also explore the advantages of embedding CI in their operation to prune some of the costs ascribed to information screening since CI provides benefits in retrieving quality information (Işık et al., 2013). In addition, SA insurance companies need to allocate resources to a dedicated CI function that conducts systematic reviews of competitive information to avoid distributing raw data (Gilad, 2015b).

In that way, SA insurance companies would bring together high-quality information and improve the quality of decision-making outcomes (Markovich et al., 2019). Since the dissemination of web information is rapid and relies on low costs, its use enhances the quality of CI information available for decision-making (Teo & Choo, 2001). Therefore, information users should evaluate the information quality entrenched in comments and timeliness dimensions of information providers (Hussain et al., 2020).

Also, leaders of the South African insurance companies must embed a corporate culture that evaluates web information resources and ensure that information providers deliver timely quality in quest of fast-tracking the development of CI in organisations (Sarraf & Esfahani, 2020). Therefore, a CI awareness and competitive culture will ensure that CI is performed optimally throughout the organisation and lead to quality CI production.

Moreover, leaders of SA insurance businesses must promote CI awareness among all employees because employees who are aware of CI actions are less likely to share information with competitors (Nenzhelele, 2015).

Leaders of SA insurance companies must also educate employees on CI and its benefits to the company. This will address the sourcing of quality information and help facilitate CI's smooth development (Nenzhelele, 2015).

Inevitably, SA insurance companies need to ensure that every phase of the CI process produces quality CI to the entire organisation's value chain to circumvent information overflow from web information sources that often mix information of different levels of quality. Congruently, Markovich et al. (2019) found that information overload obstructs organisations' decision-making ability and, as a result, can harm performance.

For that reason, Nenzhelele (2015) concluded that most organisations were clueless concerning CI quality assurance. As information overload results in some of it not being relevant and challenging for users to extract, SA insurance companies should invest in a capability that refines this information to support decisions (Markovich et al., 2019).

8.4.6 Information Credibility

The credibility of information adds more value to organisations since it makes a good impression on the customer, accelerates trust, and increases customer satisfaction and loyalty (Jamal et al., 2021). Therefore, leaders of the CI departments need to take all necessary steps to ensure the quality and credibility of CI. This study found that credible CI was not dependent on the credibility of information sources.

Furthermore, this study's finding demonstrated that as employees collect intelligent information, a lack of analytical skills and adequate processes to monitor and maintain credible information have a bearing on CIE because of poor quality assurance.

Nenzhelele (2015) concluded that most enterprises were uninformed concerning CI quality assurance. SA insurance companies can still benefit from embedding CI to unlock large volumes of raw data into actionable insights. SA insurance companies should ensure that information and sources are checked and evaluated for credibility through a quality assurance process.

So, SA insurance companies need to invest in their intellectual capital and develop a systematic process that collects, analyses and examines environmental information on rivals, customers, suppliers, and trends in the competitive intelligence industry (Karimi & Eshaghi, 2018).

Consequently, organisations with entrenched systems that monitor their competitors' activities can perform better when determining their differentiation strategy based on product quality (Calof et al., 2018).

Moreover, the information analysis of SA insurance companies should be thorough in creating genuine, quality data, be active in data collecting, and possess strong analytical abilities. In this sense, qualified analysts engaged in information collection can perform quality assurance on information credibility. In addition, SA insurance companies must ensure that information analysts accurately sort, capture and securely store the collected information.

Given that CI staff are vital in identifying the quality source of information and its credibility, employees must foster relationships with different subcultures to analyse competitive information from different cultures efficiently. In doing so, SA insurance companies will acquire coordinated and credible information, increasing their knowledge capital and improving their business performance.

Karimi and Eshaghi (2018) have shown that cultural intelligence impacted the CI of knowledge-based organisations. Therefore, SA insurance companies should train their employees to monitor different aspects of subcultures to acquire reliable and consistent inter-cultural knowledge, thus creating competitive strategies that enhance the organisation's CI (Karimi & Eshaghi, 2018). Furthermore, every person participating in the creation of CI in South Africa should be thoroughly taught, assessed, and rewarded for producing high-quality, trustworthy CI.

These experts should gather, analyse, and process external and internal information to generate the actionable intelligence that aids the organisation's strategy and decision-making processes (He et al., 2015). Equally, websites contain company information which includes sales and promotion information. This web information presents a good source for organisations to monitor CI (Tan et al., 2002). Therefore, leaders of SA insurance companies need investment in information analysis to ensure that credible and quality information flows throughout the organisation to enable leaders to make effective decisions.

In so doing, leaders of the CI units must take all necessary steps to ensure that CI analysts are involved in information collection and have the analytical skills to evaluate and handle vast amounts of information. Moreover, leaders must create a culture of verifying and validating information collected for CI (Nenzhelele, 2015).

In addition, leaders of SA insurance companies must ensure that CI professionals are equipped with preventive tools that will assist them in avoiding mistakes during information analysis and help them constantly monitor certain websites and web pages for related information.

8.4.7 Information Accuracy

As big data about the environment increases, organisations are under increased pressure to produce relevant information about the environment (Vriens, 2004). Information accuracy provides critical factual information without biased commercial interests (Storino et al., 2016).

With the digital age bringing large volumes of data, organisations must collect data and information quickly and accurately from highly dynamic markets (Sundiman, 2018). This study found that information inaccuracy positively correlated with CIE. Therefore, inaccuracy of information impacts the quality of decision-making.

McCardle-Keurentjes, Rouwette and Vennix (2008) showed how leaders' unequal distribution of information impacted their decision-making quality. CI professionals in SA insurance companies are responsible for developing a systematic programme articulating intelligence needs. These professionals should collect, analyse, and process external and internal information to produce actionable intelligence that supports the organisation's strategic and decision-making process (Du Toit, 2015; Jeong & Yoon, 2017).

CI professionals in SA insurance companies need to filter the information during acquisition to prevent the inaccurate flow of information across the organisation. In so doing, CI professionals should consider methods, procedures, and techniques tailored for the information activities embedded in CI and relevant to the context in which CI manifests in a manner that minimises failures (Maungwa & Fourie, 2018b).

Since CIE is a capability that requires the organisational culture of an organisation to be intelligence-driven, employees of SA insurance companies should contribute to the organisations' intelligence network through insights, information or any other resources and capabilities they possess.

Leaders of the SA insurance companies need to create and embrace a CI organisational culture. In this manner, leaders of SA Insurance companies should drive and own the legitimacy and importance of CI activities within their organisations (Markovich et al., 2019).

Furthermore, leaders must ensure that employees understand the importance and benefits of CI efforts to improve resource access from external and internal sources of information through the development and effective deployment of a CI system that will improve the accuracy and quality of information dispersed throughout the organisation (Jasima et al., 2020). This recommendation validates that SA insurance companies should embed systems that monitor competitor activities and information accuracy, quality, and relevancy.

Concurring, Calof et al. (2018) pointed out that organisations with a system that monitors their competitors' activities perform better when they predicate their differentiation strategy based on product quality. Jasima et al. (2020) showed that CI could be utilised fruitfully as an antecedent of organisational performance.

8.4.8 Information Usefulness

Currently, organisations rely on web resources in their decision-making processes due to their accessibility, cost reduction, ease of use and relevance in sourcing information needs (Wong & Saunders, 2020). Most organisations have invested in an internal unit dedicated to collecting, analysing, and disseminating web information to improve information use throughout the organisation (Sarraf & Esfahani, 2020).

This research showed that information usefulness positively correlated with CIE. This study's finding signifies that leaders of the SA insurance companies find more value from the information collected from CI to anticipate changes by competitors and the industry.

Furthermore, they use this information to learn about the external environment and cope with the challenges and opportunities presented by the competitive business environment. Concurring, Aramide and Adebisi (2018) identified that information use significantly assisted organisations in dealing with challenges and improving their productivity and performance.

Moreover, this study illustrates that leaders of SA insurance companies use the knowledge acquired from CI to formulate fact-based actionable decisions. In this manner, they use this information to minimise exposure to risks and deliver value-added services to the customers to improve organisational performance.

Considering that the management of information is essential for the performance of the SA insurance companies in the fiercely contested industry, CI provides foresight that positions the SA insurance sector globally. The management and distribution of CI information in organisations create a competitive advantage for the SA insurance companies to develop new products and services driven by demand on the market.

Importantly, leaders of SA insurance companies need to understand the significance of CI and allocate enough resources or budget for the operation of the intelligence unit to avoid poor management and usage of knowledge obtained from information (Aramide & Adebisi, 2018).

The allocation of resources dedicated to a CI function will assist organisations with reviewing competitive information to prevent irrelevant data from being distributed throughout the organisation (Gilad, 2015a). In that way, SA insurance companies will have reliable data to meet evolving demands of insurance products and services, solve complex issues, and react quickly to changing customer needs and demands.

Additionally, SA insurance companies leaders need to consider allocating internal organisational resources and subcontracting with external consultants that can provide them with compact and analysed relevant information to improve the use of this information across the organisation and CI practices (Markovich et al., 2019).

Moreover, leaders of the SA insurance companies must ensure that all employees are trained on CI to report relevant and useful information for decision-making (Ncube & Ndlovu, 2015). Equally important, top management of SA insurance companies must encourage the development of information culture by favouring the installation of suitable infrastructures, supporting the adoption of information technology, rewarding the usage of available facilities, and personally utilising them extensively.

Besides, the importance of the senior manager's role in supporting or disregarding information-related operations, particularly in developing or strengthening existing information infrastructures, has been demonstrated (Correira & Wilson, 2001).

Meanwhile, the organisation's management is critical to the performance of CI. Top management of SA insurance companies must model and inspire their organisation members and promote an innovative culture to implement strategic plans (Taun, 2013; Ramaseshan, Ishak & Kingshott, 2013).

In so doing, managers of the SA insurance companies need to deploy organisation resources and align them with the employees that significantly impact the successful implementation of CI (de las Heras-Rosas & Herrera, 2021). In that way, they will acquire beneficial information at a lower cost than getting information that is only helpful to the organisation. The latter is difficult, if not impossible, to obtain without simultaneously acquiring information useful to competitors (Bagnoli & Watts, 2015).

8.4.9 Competition

As the business environment becomes more dynamic and knowledge-based due to the global competitive environment, leaders need to anticipate competitor actions and act faster to solve complexity. Leadership can, however, make good forward-looking competitive decisions with CI (Hall & Bensoussan, 2007).

Even if CI can forecast potential problems in the external environment and provide solutions, this study indicated that CIE did not support the needs of the SA insurance companies to stay ahead of the competition.

This finding signifies that leaders of SA insurance companies are overwhelmed with the information they receive from the competitive environment. However, they are not using CI to access information and intelligence needed to make good competitive decisions when they need it.

Given that CI provides organisations with insights into competitors' actions and intentions, SA insurance companies need to be proactive and use CI to neutralise potential threats and defend their market share. In so doing, SA insurance companies can leverage CI to anticipate dynamic change and exploit various opportunities (Sundiman, 2018).

Concurring with this recommendation, de las Heras-Rosas and Herrera (2021) postulated that CI ensures that organisations continuously grasp the business and industry environment to learn from competitors' corporate and business strategies. Additionally, SA insurance company leaders must embed CI in their organisations as it will assist them with identifying and responding to the operational environment's challenges, opportunities, and risks (Calof & Sewdass, 2020).

Furthermore, leaders of the SA insurance companies need to use CI effectively to gather competitor and market intelligence and formulate strategies based on this intelligence to gain a competitive advantage. In addition, leaders of SA insurance companies need to use CI effectively and proactively to track the companies' competitive positions.

In that way, CI will provide leaders of SA insurance companies with timely, reliable information about the competitor and potential competitor actions and what they are likely to do to respond and make strategic decisions.

Since CI controls information and knowledge within the organisation and its network, SA insurance companies need to use CI to help them adjust their strategy to the new paradigm of competition. This recommendation aligns with Hussein et al. (2011), whose study showed that gathering information had a significant relationship with CI.

8.4.10 Customer Insights

Globally, insurance companies struggle with collecting and analysing past customer life cycle information and interpreting events required for CI in the insurance industry (Kwach, 2018). This study showed that customer insights did not significantly impact CIE.

Furthermore, this study has indicated that even though the insurance industry is unpredictable, leaders of SA insurance companies are not widely utilising CI for understanding big data and predictive analysis to make informed decisions. Moreover, most insurance companies continue to duplicate traditional products and services that provide no solution to customer needs, resulting in fewer customers taking part in these solutions (Oyomo, 2019).

This study denotes that SA insurance companies experience challenges using published and non-published information, resulting in their ability to solve complex problems, react quickly to the customer life cycle, and drive efficiencies (Oyomo, 2019). Insurance companies in South Africa could utilise CI to improve productivity, allowing them to cope with their extensive client base, customer-focused intelligence, and competitive data, therefore growing their CI.

As CI transforms valuable information and data into intelligence about customers and the competition, SA insurance companies need to gather customer intelligence rather than focusing solely on the competition. So, SA insurance companies should engage more with their customers through product opinions and reviews because data from customer opinions and reviews are an essential information source for CI (Amarouche et al., 2015; Xu, Liao, Li & Song, 2011).

This recommendation concurs with some studies showing that consumer purchasing decisions were influenced by ratings and reviews, and business performance increased as a result, including market perceptions, profitability, and satisfaction among business owners (Bai, Marsden, Ross Jr & Wang, 2017; Nieto, Hernández-Maestro and Muñoz-Gallego, 2014).

With customers more likely to compare several competitive products with similar products from the competition, SA insurance companies need to embed CI to assist them in analysing and exploiting these opinions by identifying competitor risks and threats in time for leaders to make strategic decisions (Amarouche et al., 2015; Xu et al., 2011).

Equally, customer communication changes result in posting comments, suggestions, reviews, and recommendations about products or services on review sites and social networking platforms. In this way, customers pursue more information about products or services to maximise their satisfaction, expectations, and experiences (Hussain et al., 2020). Additionally, customers search for information from informative and authentic sources and online reviews on online communities and platforms (Cheong & Morrison, 2008).

Leaders of the SA insurance companies should therefore be more proactive in learning as much as possible about customers' opinions on their products and services in general and customers' opinions on identical products and services from their competitors to get ahead of their activities (He et al., 2015).

Since eWOM is persuasive communication that influences individual customers and organisations, it increases the company's products, brand reputation, and social interactions. In tandem, eWOM gathers information about products or services (Nieto et al., 2014; Lu, Ba, Huang & Feng, 2013). Therefore, SA insurance companies leaders need to embed an organisational culture that drives business performance, strategy and knowledge transfer for eWOM to communicate with customers by replying dynamically to online reviews associated with management (Hussain et al., 2020).

Hughes et al. (2013) consistently demonstrated that customer CI sharing was influenced by salesperson customer orientation, customer-centric extra-role behaviour, and relationship quality. Additionally, leaders of SA insurance companies need to consider social media CI activities in their formal business process to anticipate and face future challenges and enhance their capabilities to maintain a competitive edge over their competitors (Ross et al., 2012).

CI activities could therefore assist SA insurance companies in developing new products and services, optimising business processes, enhancing value creation, and fostering innovations. Notably, the increase in business knowledge and innovations will lead to a rise in economic activities, significantly impacting today's knowledge economy (He et al., 2015).

8.4.11 Technology

Big data's knowledge and value increase the sophistication of technology to gather and diffuse information, while CI analyses intelligent information and provides competitor insights for effective decisions (Gilad, 2016). This study demonstrated that CIE did not significantly impact technology readiness. Furthermore, this study signifies that SA insurance companies are lagging with IT capabilities and infrastructure that effectively support CI or are not integrating the appropriate technologies that support their CI activities to unlock large volumes of raw data into actionable insights.

Given that technological superiority provides numerous opportunities for businesses to obtain data from internal and external sources, SA insurance firms must invest in technology that gathers, saves, and analyses large amounts of data (Zhu et al., 2014).

Therefore, SA insurance companies cannot develop a realistic picture of their technology position without technology intelligence. Since the quality information gathered on current and future technology trends strongly influences organisational technology management effectiveness, SA insurance companies need to integrate technology intelligence into CI.

So, SA companies can benefit from applying competitive intelligence to unlock big raw data into actionable insights. Consistent with this recommendation, Rudolph et al. (1991) showed that most companies had reaped the benefits of CI as they realised the power of technology in their businesses to reduce risk and unleash other opportunities.

Furthermore, CI will assist SA insurance companies with combining customer value innovation and technology intelligence to increase their sustainable growth and profits (Koriyow & Karungu, 2018).

As every technology adoption process is uncertain, leadership commitment is needed to increase resources to deal with risks. Top management of SA insurance companies should have the willingness and financial resources to employ and support skilled employees to ensure the adoption and desire to use various technological innovations within organisations (Angeles, 2013). Congruently, Lian et al. (2014) showed that financial resources positively correlated with adopting cloud computing in Taiwan.

Equally, leaders of SA insurance companies should consider partnerships with vendors to enhance technology adoption since technology vendors will enable efficiency in adopting technology across the organisation (Ahmadi et al., 2015).

This recommendation correlates with Duh and Fabiao (2018), who showed that financial and vendor support had a significant impact attributed to support from technology vendors assisting organisations with lessening and mitigating lack of internal technical expertise and skills (Ismail & Ali, 2013).

8.4.12 Information Providers

With the internet playing a fundamental role in supporting an organisation's intelligence activities, organisations use it to gather and disseminate intelligence information for decision-making and to remain globally competitive (Uzohoue & Yaya, 2016). Information providers play a significant role in CI because they manage explicit knowledge and collect raw data for the organisation to attain a competitive advantage (Uzohoue & Yaya, 2016).

Information providers are therefore renowned for sourcing information impacting the development of CI within the organisation. Furthermore, information providers play a vital role in the quality control of information during the gathering process since they focus on organised CI (Sarraf & Esfahani, 2020).

This study showed that enduring relationships with information providers correlated significantly with CIE. Furthermore, this finding indicates that SA insurance companies heavily rely on experts outside their organisation to provide quality information for their CI function to combine secondary sources outside the organisation with internal information for strategic decisions (Calof, 2017b).

This finding also indicates that SA insurance companies collaborate with information providers because of their creative and unique methods of retrieving quality web information.

SA insurance companies' CI function interprets this quality information from outsourced collectors for strategic decision-making (Gilad, 2016). Consistent with this view, Markovich et al. (2019) showed that CIE positively impacted the perceived quality of web information sources and alliances with information providers. Therefore, information providers provide SA insurance companies with critical, relevant, and trustworthy information for strategic decision-making.

SA insurance companies then need to build enduring relationships with information providers to promote the image of organisations and achieve their stated goals. Consistent with this recommendation, Markovich et al. (2019) showed that an organisation’s relationship with information providers was positively associated with CIE.

Uzohue and Yaya (2016) also emphasised that information professionals are relevant for organisations since they have adopted creative and unique methods of retrieving information from the internet and can assist organisations in using this information to promote their image and achieve their goals.

Given that organisations consistently need intelligent information, information providers can assist SA insurance companies with intellectual aspects of searching for specific information from the internet, gathering CI and providing research services to enable top leadership to make strategic decisions (Uzohue & Yaya, 2016). Therefore, the top leadership of SA insurance companies should integrate information providers into organisations' business processes so that they are familiar with events that affect the business and can offer solutions to identified challenges and problems.

However, the top leadership of SA insurance companies needs to consider the information professionals' skills and assess the scope of their involvement and responsibility towards delivering CI. Havenga and Botha (2003) consistently pointed out

that organisations should consider evaluating the amount and type of information professionals' engagement and duties in delivering CI.

Since organisations require organised CI, information providers should meet the needs of various information users in SA insurance companies and assist them in identifying various strategies such as web mining to capture big data and online resources.

In so doing, web mining can help SA insurance companies to retrieve, process, and capture information from web pages and documents on the Internet (Silva, Pacheco, Negrete, Niño, Lezama & Varela, 2019). Furthermore, information professionals need the foresight to know what sources are most relevant and must pass this advice on to SA insurance companies.

Equally important, information providers can help turn information into intelligence by assisting SA insurance companies in managing their information (Diyaolu, 2019). In that way, insurance companies in SA will have immediate access to information on new goods, technology, and ideas generated by suppliers, allowing them to implement service innovation quickly. CI will convert information from web mining into knowledge about a group of competitors, which various departments within the organisation can use to make strategic decisions (Adidam et al., 2012).

SA insurance companies should strengthen cooperation with information providers since innovative providers assist organisations with competitors, customers, and new insights for new services. This recommendation aligns with Markovich et al. (2019), who pointed out that enduring relationships with information providers enhance CIE development.

Equally, SA insurance companies should consider outsourcing part of their CI activities to information professionals since they have good analytical skills and experience dealing with database vendors. Also, information providers know where to look for information and have developed questioning skills to search terms in databases to determine what specific information they require. This partnership will assist SA insurance companies with leveraging big data and creating more value and customised products for their existing and potential clients.

8.4.13 Employee Role Clarity and Competitive Intelligence Embeddedness

Role clarity is essential to employees as it determines how well tasks are accomplished and, consequently, an employee's performance. Therefore, the organisational climate affects the employees' perception of their role clarity (Mishra & Kumar, 2019). The results of this study indicated that employee role clarity did not influence CIE.

Most of the competitive information is sourced from the company's employees, who get updated information on industry activities (García et al., 2009). Furthermore, this finding highlights the lowest organisational climate in the SA insurance companies, exhibiting role ambiguity that creates stress among the employees to provide intelligent information for organisations. Also, this finding indicates the existence of leadership styles, participation in decision-making, and how leaders of the SA insurance companies provide challenging jobs to employees and reduce boredom and frustration.

Considering that employees are the primary sources of CI in organisations, this study indicates that it is difficult for insurance businesses in South Africa to encourage and engage their personnel in CI initiatives. SA insurance businesses should foster a climate where workers view their roles more explicit.

With continuous industry change that may disrupt role clarity and organisational structures, leaders of the SA insurance companies should promote an organisational climate that measures employees' perceptions or feelings about their respective organisations. This will assist them in identifying roles that increase the stress levels among the employees.

Furthermore, leaders of SA insurance companies must increase employee job clarity by regularly reiterating work objectives and expectations (Hassan, 2013). Leaders of the SA insurance companies should also cultivate innovative work behaviour by encouraging knowledge sharing among employees by clearly identifying their roles.

Moreover, leaders of SA insurance companies should also empower employees, communicate, and inform them of information that needs to be collected to ensure that employees regularly contribute CI information for making strategic decisions.

Jada, Mukhopadhyay and Titiyal (2019) consistently supported that role clarity has a mediating impact in empowering leadership and information sharing. Furthermore, Jada et al. (2019) observed that role clarity strengthened the indirect relationship between empowering leadership and innovative work behaviour.

While research by Hemanth Kumar and Premchand Babu (2017) found that role clarity, continuous change, and the diversified workforce were the reasons that led to workplace complexity, as quoted mainly by the IT employees. Furthermore, their study showed that role clarity and autocratic leadership led to complexities in non-IT companies.

Therefore, SA insurance companies' leaders should support employees and provide them with enough information to deal with new challenges and perform everyday tasks (Samie et al., 2015). In addition, SA insurance companies should develop a CI skills and capabilities framework that clearly defines roles. Consequently, this will assist organisations in determining the roles and responsibilities each individual has to undertake and provide role clarity among the employees.

Given that CI is likely to be produced by employees from different business units, leaders of the SA insurance companies should encourage employees to collaborate more effectively to share the knowledge among themselves to generate outputs that support their strategic management duties.

Additionally, leaders of the SA insurance companies should train employees and upskill them with basic CI skills to effectively collect the organisation's CI needs without duplicating information already available within the organisation (Du Plessis & Gulwa, 2016).

These executives should also implement effective CI programs to provide staff with the analytical abilities, knowledge, and authority needed to deal with complex information. Equally, leaders of SA insurance companies need to develop a compelling vision for the organisation and define employees' roles that positively impact on abilities of teams to succeed (Lynn & Kalay, 2015).

In so doing, leaders need to highlight their employees' roles and responsibilities, what aspects are essential, and how delivering the duties of the functions will help the organisations achieve their goals and success (Thangavelu & Sudhahar, 2017).

Since employee role clarity improves job satisfaction and performance, leaders of SA insurance companies need to focus on employee engagement and align employees with the organisational goals to enhance the teams' productivity to source intelligent information to contribute to the organisation's success.

Because leaders are essential providers of job-related information and feedback for workers who influence their work process and behaviour, role clarity boosts the availability of knowledge and other resources.

8.4.14 Employee Role Clarity and Organisational Performance

Role clarity improves job satisfaction and employee job performance. Organisations with structured role definitions are very influential in improving employee and organisational performance (Mishra & Kumar, 2019). The study's result showed that employee role clarity significantly impacted organisational performance. Furthermore, this result highlights the prevalent leadership styles that drive organisational performance and employee productivity in SA insurance companies.

Considering that leadership determines the success and failure of organisations, SA insurance companies should adopt leadership styles that enhance the capabilities and abilities of the people. Therefore, SA insurance companies' leaders should embrace participative and transformational leadership since they are more likely to create an atmosphere of motivation among their employees (Alghazo & Al-Anazi, 2016).

In so doing, leaders of SA insurance companies should influence employee engagement by building profitable relationships with employees and unleashing their potential to attain organisational performance. This recommendation concurs with Osborne and Hammoud (2017), who showed that the bond between leaders and employees increased employee engagement and organisational profitability.

In addition, leaders of the SA insurance companies need to direct and motivate employees to achieve organisational goals and improve organisational performance. In conformity with this recommendation, Bersin (2014) posited that the longevity of an organisation is affected by employee engagement, which is a factor in the organisation's financial performance.

Therefore, the SA insurance companies' leaders should create an enabling environment and an organisational climate that fosters self-belonging, encourages employees' diverse views, and allows them to be part of the decision-making process.

Equally, leaders of SA insurance companies need to focus on employee engagement and align employees with the organisational goals to enhance the teams' productivity to contribute to the organisation's success. This means that leaders of the SA insurance companies should have the ability to connect emotionally with employees to influence employee engagement to maintain the organisation's profitability since engaged employees deliver improved organisational and individual performance (Kortmann et al., 2014).

Furthermore, the SA insurance companies' leaders should continuously shape employees' attitudes and behaviours for responsive business performance (Fisher et al., 2010), and they should empower employees with structured tasks to ensure that employees are more personally accountable and engaged in work processes. Leaders of the SA insurance companies should give autonomy and support to employees to promote employees' behaviours that are favourable for the organisation due to their feelings of self-efficacy and psychological ownership (Osborne & Hammound, 2017).

Concurring, Kim and Beehr (2017) found that empowering leadership has a positive relationship with self-efficacy and psychological ownership while negatively impacting deviant behaviour. Therefore, leaders of the SA insurance companies should create a safe workplace for employees to be enthusiastic in work-related activities and improve employee engagement to ensure employee alignment with the organisational goals to deliver on organisational outcomes.

Given that leadership skills have a more substantial effect on job satisfaction than leadership behaviours, leaders of the SA insurance companies should display fundamental leadership skills that increase employee job satisfaction in the workplace.

8.4.15 Competitive Intelligence Embeddedness and Customer Satisfaction

Competitive market measurements must prioritize addressing customer wants, and the ultimate purpose of any CI process is to improve organisational performance while increasing customer satisfaction (Baker & Sinkula, 2009). This study established that CIE is an essential factor influencing customer satisfaction in SA life assurance companies. Furthermore, this finding shows that SA insurance companies are paying more attention to CIE-related factors that improve customer satisfaction. This result demonstrates that SA insurance companies benefit from using CI to gain actionable customer insights assisting them in forming intimate relationships with customers to increase their satisfaction and loyalty.

As customer knowledge is likely to affect their satisfaction and interfere with the relationship between satisfaction and loyalty, SA insurance companies need to pay attention to customer knowledge. Therefore, SA insurance companies should consider CI to monitor customer behaviour, track customer buying trends and surveys, and perform in-depth customer analyses (Muller, 2006).

In doing so, SA long-term insurance companies can benefit from applying CI with a combination of technological innovation by integrating customer experience centricity with new technologies. Additionally, leaders of SA insurance companies should make suitable investments in technological innovation to improve customer experience. Concurring with this recommendation, Oyomo (2019) concluded that integrating customer experience centricity with new technology to drive customer experience affected the use of CI in Kenyan insurance companies.

SA insurance companies should combine customer value innovation with customer experience centricity to continue enjoying sustainable CI activities. In doing so, they should employ CI to gather customer-focused intelligence and competitive information

from their extensive client base by combining the organisation's resources to create more customer value (Blenkhorn & Fleisher, 2001; Gračanin et al.,2015). In addition, SA insurance companies need to use the information gained from the knowledge of CI to enhance customer satisfaction.

By creating intimate client interaction to the point where customer demands dominate all workers' thoughts, it will respond and produce continuous learning about consumers and markets. Equally important, top management support and commitment are needed to implement measurement and reward systems linked to customer satisfaction.

This recommendation suggests the importance of creating and keeping a high level of CI organisational culture (Markovich et al., 2019). A high level of CI culture will assist employees in identifying the important aspects of customer and competitor information (Sarraf & Esfahani, 2020).

Top management of SA insurance companies should ensure that CI capabilities are entrenched in enterprise-based processes throughout the organisation to encourage collaboration between service personnel and the CI team to pick up on any valuable information from customers, including their comments about products and services.

SA insurance companies should also develop CIE capabilities that provide leaders with crucial data regarding changing customer needs and preferences to help build stronger customer relationships through advanced decision-making.

Furthermore, SA insurance companies should employ CI to understand customer analytics and take advantage of the opportunities within the customer value chain to create products and services that meet customer requirements (Porter & Kramer, 2019).

In addition, leaders of SA insurance companies can use CI to improve customer experience by analysing customer information to identify preferences and make communication and customer relationships more meaningful. Since CI gathers customer intelligence, SA insurance companies' leaders can use insights from CI to customise products and services to satisfy customer needs.

This will enable SA insurance companies to customise the shopping experience, adding value to the consumer and increasing brand satisfaction. Moreover, SA insurance companies should measure customer experience centricity and ensure it aligns with their needs to maximise profits.

Moreover, SA insurance companies should use customer value centricity to increase their competitiveness in the market. Additionally, SA insurance companies should be more vigorous in establishing customer value and customer experiences that affect their CIE.

8.4.16 Competitive Intelligence Embeddedness and Organisational Performance

CI intelligence impacts the company's performance with the mediating role of customer satisfaction. Using the information gained from the knowledge of CI intelligence has increased customer satisfaction and thus increased financial performance for the company (Sarraf & Esfahani, 2020, p.1).

This study showed that CIE significantly influenced organisational performance in SA insurance companies. This finding signifies that SA insurance companies embedded CI to gain more knowledge about environmental changes and took advantage of market opportunities to improve their performance.

With CI scanning the environment and obtaining market information for organisations to improve their competitive position, leaders of insurance companies need to collect information about market sectors to achieve market performance. Concurring with this recommendation, Muritala and Ajetunmobi (2019) opined that organisations should entrench CI continuously to identify market opportunities, giving them an edge over competitors. Furthermore, leaders of SA insurance companies should exploit CI activities and use them to improve organisational performance.

In conformity with this recommendation, Magasa et al. (2014), and Stefanikova et al. (2015) found that the implementation and utilisation of CI enhanced performance and affected the sustainable growth of an organisation. Essentially, leaders of SA insurance companies need to instil the fundamental values founded on understanding and

responding to the needs of customers and the necessity to search constantly for new opportunities in the market (Irenaus et al., 2021).

Equally, leaders of SA insurance companies should consider CI use to assist them in understanding their organisational environment and design the best strategies to adapt to it. Concurring, Salguero et al. (2019) found that CI use was affected by organisational and environmental characteristics through CI effort. Meanwhile, CI enhances internal communication, knowledge, and strategic plans to increase organisational performance (Salguero et al., 2019; Ezenwa et al., 2018).

When applied by management and employees, CI facilitates knowledge transfer throughout the organisation. Markovich et al. (2019) also agreed that CIE happens when there is a collaboration among management and employees to transfer knowledge in the organisation.

As organisations rely on daily information from web sources, SA insurance companies should invest in a dedicated unit specialised in collecting, analysing, and distributing web information. Congruently, Sarraf and Esfahani (2020b) posited that companies rely on data from such resources daily. Vriens (2004) opined that many organisations are currently implementing a CI function that collects and processes relevant environmental information in a structured fashion. While web-based information and social media are obvious sources of CI, leaders rely on web-based information in their strategic assessments and day-to-day operations, such as periodic competitor evaluations, daily marketing, and competitive newsletters (Markovich et al., 2019).

Therefore, leaders of the SA insurance companies must systematically and continuously collect and analyse market information to respond better to market changes, increase marketing effectiveness, and improve organisational performance (Shahbandi & Farrokhshad, 2019). These leaders also need to leverage their relevant web information resources to support CI and decision-making by deploying them throughout the organisation's value chain to improve company performance. In this manner, leaders must allocate intra-organisational resources that analyse relevant information and develop beneficial CI practices within their organisations (Markovich et al., 2019).

8.4.17 Customer Satisfaction and Organisational Performance

Customer satisfaction is associated with the consumers' whole consumption experience, which is critical for any organisation's long-term sustainability (Neupane, 2014). Customer satisfaction is essential because customers contribute and create value in organisations to attain superior performance (Gomez et al., 2004). This study indicated that customer satisfaction impacted organisational performance in SA insurance companies.

Furthermore, this finding highlights that customer satisfaction is a critical operational goal for the SA insurance companies since they use it to measure the value created by their insurance products in fulfilling customer expectations and their needs. This finding also shows that SA insurance companies have close ties with their customers and rely on their feedback to obtain information that is more likely to impact their needs and improve their products and services.

Considering that customer satisfaction results in high sales and profitability for organisations, SA insurance companies should put clients at the centre of their activities and create more value through excellent alignment of customers and personalised customer needs, services, and satisfaction.

Furthermore, SA insurance companies should create a compelling customer value proposition that offers solutions with customers in mind rather than imposing traditional products which lack flexibility in their design. This recommendation is congruent with Oyomo (2019), who postulated that organisations failed to adapt and give solutions that their consumers requested, instead adhering to their usual products that were not popular with customers.

Moreover, SA insurance companies should use customer-focused intelligence to review their current products and services to ensure that the flexibility and design of these products and services constantly satisfy customers' needs. SA insurance companies also need to create satisfaction from existing customers and use it to increase their customer base to maximise their performance. In so doing, leaders of SA insurance companies

should ensure that employees build close relationships with their customers to enhance customer satisfaction in the long run.

Equally, leaders of SA insurance companies should continuously identify the knowledge and customer's hierarchy of needs to improve organisational performance. Concurring with this recommendation, Homburg, Wieseke and Bornemann (2009) showed that high levels of customer need knowledge are associated with higher customer satisfaction and willingness to pay.

Therefore, leaders of SA insurance companies must ensure that employees generate knowledge during their interaction with customers to improve customer satisfaction and create value for clients. Since customer service factors complement customer satisfaction, SA insurance companies should consider investing resources in customer service to increase organisational performance.

Meanwhile, customer satisfaction is a valuable tool for organisations to achieve their core business objective and performance (Odunlami et al., 2013). Essentially, SA insurance companies should improve their financial services and customer service quality and reliability by encouraging collaboration and eliminating barriers between employees and business units. SA insurance companies should likewise establish a seamless process that monitors and resolves customer complaints.

With customers applying enough pressure on insurance companies to provide and deliver cheap, innovative, and quality service, SA insurance companies need to strengthen their ability to satisfy customers and stay ahead of the competition. In this manner, SA insurance companies should employ new technology and modern artificial intelligence tools to create customer satisfaction and maximise profit. Moreover, leaders of SA insurance companies should embed multiple quality management practices to improve productivity and customer satisfaction.

9. Contributions of the Study

This study made theoretical and practical contributions, which are presented in the following subsections.

9.1 Theoretical Contributions

Theoretically, this study contributes to the field of Human Resources (HR), Knowledge Management (KM) and Organisational Behaviour (OB). Organisations and researchers have focused on collecting competitive information but rarely examine the factors driving employees and managers to incorporate the collected CI in their decision-making to gain a competitive advantage (Markovich et al., 2019).

This study contributes by developing an integrated conceptual model, whose empirical testing will expose a wide range of factors that can drive the incorporation or embeddedness of CI by companies' employees, especially in the competitive insurance industry. The study also extends previous models of CI through the inclusion of drivers and outcomes of CIE.

The developed integrated conceptual model can be used for studies in HR, KM and OB to understand what drives the adoption or the embeddedness of innovative or competitive information in decision-making in these disciplines' various areas of study. The empirical testing of the developed integrated model will provide rich insights for practitioners in the life insurance companies in South Africa and other countries.

This study will thus make practical contributions to the life insurance industry by exposing various dimensions of factors that can help or hinder firms in the industry from embracing competitive information for employee, customer, and general organisational benefits.

Additionally, this research project contributes by linking CIE with various variables. Integration of these variables draws attention to the process of strategic management best leading to organisational performance. Most CI studies have focused on gathering and disseminating information, plus strategic management tools to scan the environment and analyse market trends for effective decision-making.

Although some studies emphasised that CI plays a critical role in strategy development and formulation disciplines, Markovich et al. (2019) contend that studies with models that understand the drivers and outcomes of CI-related capability were lacking.

Importantly, this research has added to a body of knowledge as a wide range of peer-reviewed academic articles have been published by authors from North America and Europe concerning the subject field, particularly the insurance industry.

This suggests few from South Africa consider this subject field, confirming the statement by Du Toit (2015, p.18) that the most productive authors are academics teaching CI at institutions of higher learning. Consistently, Adidam et al. (2012, p.243) posited that most of the conceptual development of the CI literature was from the developed market perspective.

Moreover, the researcher has noted methodological limitations in peer-reviewed academic journals. Firstly, most studies are exploratory, signifying that the research findings cannot be generalised.

With data analysis and discussions from a single case study, the results cannot be generalised to other industry sectors, even if other organisations could benefit from the research. Secondly, the literature reveals that most studies used content analysis to establish research patterns in the subject field.

While this method is flexible, permitting a wide range of analytic options, it only describes what is there and may not show the underlying causes and effects of the research pattern. Consistent with these views, Maritz and Du Toit (2018) observed that thematic content analysis had limited interpretative power. This denotes that such research studies could have benefited from triangulation using other methods.

Thirdly, the researcher also found that studies employed the convenience sampling technique in most surveys. This potential limitation could lead to some important participants being left out of the survey. The researcher accepts that this study will fill a gap in academic knowledge and benefit organisations, managers, employees, business practitioners, and industry stakeholders at large.

For this reason, the researcher maintains that top management structures of SA life assurance companies will have a vested interest in this research project as the use of CI has become a business imperative in the new digital economy. Additionally, the results from this project have shed light on the critical drivers of CI for organisations to exceed performance.

This study presented hypothetical relationships between constructs based on seventeen variables. The researcher established the relationship between the constructs and provided logical explanations for and predictions regarding these relationships in the real world.

9.2 Practical Contributions

Notwithstanding this current study's limitations, it contributes to theory and practice in multiple ways. This study contributes to the competitive intelligence embeddedness debate by linking it with various variables and exploring its relationship with its overall performance, as few studies have done before (Markovich et al.,2019; Sarraf & Esfahani, 2020).

Furthermore, the contributions and related findings that emerged in this research and the conceptual framework are relevant for practice to guide top managers in ensuring that their organisations have structured processes to acquire accurate, credible, and quality information usable for strategic planning decision making.

This conceptual model will also assist top management in setting up a dedicated competitive intelligence function by defining its role and practices and clarifying employee roles. Moreover, this conceptual model will assist top management with ensuring that these functions are carried out formally with specialized personnel with critical thinking, analysing information, marketing, and research skills, including strategic thinking, leadership, management and communication (Mabe et al., 2019).

In addition, this study's conceptual model can be widely used by decision-makers across all sectors, including SA insurance companies, to understand data and predictive analytics to make informed decisions.

SA insurance companies can benefit from applying this research model to unlock volumes of raw data into actionable insights, provide a complete picture of the evolving demand for insurance, and offer solutions that customers desire. Equally, this study's research model can provide organisations across different sectors with better insights that will enable them to gain a more holistic view of their performance.

Lastly, this study is essential for managers in the insurance sector and other industries since it will assist them in entrenching competitive intelligence practices in their respective organisations to achieve a competitive advantage. Future researchers can use this study and its conceptual model to reference other related topics.

The study highlighted other vital relationships in the conceptual model that require further research: leadership, structure and process, customer insights, competition, technology, employee role clarity, competitive intelligence embeddedness and accuracy, credibility, and quality of information.

10. Limitations of the Study and Recommendations for Future Research

This section presents this study's limitations and corresponding suggestions for future research.

10.1 Limitations of the Study

This study has reached its aims and objectives, although there were some unavoidable limitations. The researcher has made considerable efforts to ensure that this study's conceptual and methodological aspects meet the research standards and are as precise as possible. The limitations' probable causes and effects on the current research are outlined below. These disclosures are not intended to diminish the study's findings but rather to provide a more apparent platform for future studies.

Firstly, the study focused on the SA life assurance industry, reflecting geographically comparable populations with similar exposure to the factors in the external business environment.

Although other organisations may benefit from the results of this study and its research model, this study did not include the short-term insurance sector and other business sectors in SA. The generalizability of the findings for the short-term insurance and other business sectors in SA, including other countries, should be treated with caution.

Secondly, this research employed a five-point Likert scale rating since it provided an interval or ratio-based scale. It still posed some limitations as some respondents indicated that the questionnaire on this rating scale was too long to complete.

Thirdly, as in any research, financial constraints-imposed limitations as research instruments were costly to purchase, thus posing a problem in finding instruments suitable for this research.

The researcher then discovered and investigated the use of Google Drive's Form tool to facilitate and process data, SPSS version 24.0 for primary data analysis, including data screening and PLS-SEM using the software package (SmartPLS 3.2.7) to analyse the conceptual research model and perform explanatory and further predictive analysis.

Furthermore, this study was cross-sectional with reflective constructs. The findings reported relating to only a particular point in time. Moreover, this approach does not consider cause and effect. Therefore, it is difficult to determine the timeline of occurrences. Also, the relationships posited in the conceptual model were only inferred rather than proven. In addition, due to cost, time, and logistical limitations, this research employed the online survey method to collect data through a simple random sampling technique.

The researcher experienced challenges as participating companies could not hand over information about employee groups due to privacy policies, which created time constraints for this research. As such, the researcher partnered with some vital corporate representatives to randomly distribute the questionnaires to the employees of targeted companies. Moreover, this study's complex model resulted in more time to analyse the detailed seventeen hypothetical relationships in this study.

The researcher then employed PLS-SEM to benefit from the elevated statistical power of the method compared to CB-SEM. Another observation the researcher has discovered is the disparity in the significance of eight hypotheses from PLS-SEM compared to eleven from SEM employing AMOS software.

Lastly, this quantitative research employed a survey using self-administered questionnaires that posed limitations, including technical difficulties. Concurring, Zikmund (2003) pointed out that respondents to an online survey generally do not all have access to the same level of technology.

With the COVID-19 outbreak disrupting organisations and adopting remote working for their employees, the participants, including the executive and senior management members, experienced difficulties due to accessibility.

Also, low-speed internet and poor bandwidth negatively impact their ability to actively participate in the research project, resulting in prolonged response time. Furthermore, some executive and senior management forming part of this study's population opined that some of the statements posted on questionnaire items were intrusive into specific core aspects of their management or that the information required was sensitive.

Some senior management regarded competitive intelligence as corporate espionage despite it being clearly defined in the letter of introduction. Concurring, Muñoz-Cañavate and Alves-Albero (2017) concluded that field studies requesting CI practices were challenging to conduct because of the inherent apprehension about disclosing such information.

Similarly, Neuman (2000) explicitly states that surveying executives and senior management challenges include difficulty with restricted access and some assistants intercepting questionnaires on their behalf. This study experienced difficulty in reaching the top management due to their busy schedules even during the COVID-19 pandemic, thus making some questionnaires returned incomplete. Moreover, some organisations withdrew their participation in this research, citing that their employees were involved in climate surveys and coping with change.

Some stated that they were distressed due to the current challenges posed by the COVID-19 pandemic. However, this research attained a response rate of 73 percent, which was acceptable for this study.

10.2 Directions for Future Research

Since the current study focused on the SA life assurance industry, it would be enlightening to study the short-term insurance sector and other companies in the different sectors of the economy to identify differences and similarities in embedding CI in their operation.

Future research may consider a similar study in other African countries and globally to find similarities in embedding CI in organisations. The study had a limited sample of 276, and the results could not be generalized outside the sample frame used.

Also, future research should consider using a large sample size as that may provide an essential advantage as a research method. Besides, significant results would be achieved with a larger sample size relative to smaller sample size.

Given this study's cross-sectional nature with reflective constructs, future studies can apply longitudinal data to examine causal links more explicitly. Furthermore, future studies can use observation research focusing on factors affecting competitive intelligence embeddedness over time.

Moreover, future studies should consider formative indicators since content validity produces satisfactory results for formative constructs because of being defined by dimensions or measures that form them (Petter et al., 2007).

Considering that this study employed PLS-SEM for its complex structural model, future research should explore SEM with AMOS and CB-SEM with larger sample sizes to achieve a different research outcome.

Furthermore, future research may extend this study to integrate other potential constructs of interest or reduce the number of constructs in the current research model. In addition, this study employed quantitative research with a non-experimental design whereby the researcher only observed and interpreted data about events in the present.

Therefore, future studies could explore experimental and mixed methods research designs that may yield different findings. As CI involves the organisation's external and internal environment analysis, this study showed that SA life assurance companies believe in competitive intelligence embeddedness. These companies lack commitment from leadership, adequate structures and processes, technology, and culture that embrace CI activities within organisations.

This study showed that sources of information of interest must be monitored for their accuracy, credibility, and quality to manage each department's needs and help in decision-making. Future research could compare the validity of these results across SA business sectors.

11. Concluding Remarks

CI is a business tool used in strategic management that is getting momentum for firms to create long-term competitive advantage (Salguero et al., 2019,1). Consequently, organisations entrench CI in their practices to assess intelligence and knowledge to survive in the competitive and complex business environment. This study aimed to investigate the effect of CIE on organisational performance in SA life assurance companies.

A primary contribution of this study was to develop a competitive intelligence strategy model for the SA life assurance industry that other industry sectors can replicate. This quantitative research surveyed 276 employees of the SA life assurance companies to test this study's integrated research model. The factors impacting CIE were assessed from seventeen hypotheses supported by a meticulous analysis. Based on the analysis of the results, this study found that CI was entrenched with relative success in some areas within the operation of the SA life assurance companies.

SA life assurance companies can gain more advantage over their competitors by embedding CI throughout the value chain of their operations. The above is needed because CI applied by management and employees enhances knowledge transfer across the organisation.

While effective CIE initiatives exist in SA life assurance organisations, formalised strategies and structures are required to attain superior competitive performance. The study echoed that CIE forms an integral part of strategic management activities in SA life assurance companies and is closely associated with customer satisfaction and organisational performance. Furthermore, the success of CIE in SA life assurance companies is influenced by the leadership style, technological readiness of the organisation, corporate culture and the accuracy and use of information for strategic decision-making.

To redress the literature imbalance, the research analysis found sufficient empirical evidence to support some of the literature reviewed in this study. Other issues emerged during the investigation, although the focus of this investigation was limited to matters that affected competitive intelligence embeddedness, customer satisfaction and organisational performance. Despite this study's theoretical and practical contributions, it has some limitations. These limitations gave rise to suggestions for future research. In the previous section, the researcher provided recommendations to address factors impacting competitive intelligence embeddedness in SA life assurance companies.

Throughout this study's data collecting and analysis phases, the integrated conceptual model was used, which may have contributed to the depth of quantitative examination of how CIE and organisational performance in the SA life assurance evolve. Future studies should replicate this research extensively and in terms of statistical samples considering these factors. CIE helps organisations develop core competencies. Once organisations reach CIE, information is translated into unique knowledge. Consequently, CIE is how CI infuses the organisation to make tactical decisions with relevant competitive knowledge to stimulate organisational performance (Markovich et al., 2019).

Therefore, this study concludes that organisational, market factors and information attributes can either facilitate or inhibit the effectiveness of CIE in organisations. Since these factors are contained in this study’s integrated research model, this study recommends that experts and researchers use this model in many contexts to benefit from embedding CI practices while carrying out operations in their organisation.

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13. APPENDICES

13.1 Appendix A: Introductory letter to participants

UNIVERSITY OF KWAZULU-NATAL
GRADUATE SCHOOL OF BUSINESS AND LEADERSHIP

Doctor of Business Administration (DBA) Research Project
Researcher: Mpho Maluleka (0824683384)
Supervisor: Dr B.Z. Chummun (031 260 8943)
Research Office: Ms C.F. Gama (031-260 7549)

Dear Respondent,

I Mpho Maluleka, student no: 218078329 a doctoral student at University KwaZulu Natal Graduate School of Business and Leadership. In partial fulfilment of my final thesis and my doctoral degree, it is a requirement to complete a research project.

The title for my research project is: "Developing a Competitive Intelligence Strategy Model for the South African Life Assurance Industry". Equally important, Dr Bibi Chummun of the University of KwaZulu–Natal, South Africa is my supervisor for this research project. As part of my data collection procedures, I am inviting you to participate in this research study.

The study is about developing a Competitive Intelligence Strategy model that will add more value to the South African life assurance industry to prosper in the new digital economy. Participation in this survey is entirely voluntary, and there are no known or anticipated risks to participation in this study. The online survey method will be used to collect data for this project.

You are kindly requested to answer the questionnaire as honestly as possible. This online survey will take approximately 25-30 minutes of your time to complete. There are no correct or incorrect answers to the responses, and the views you express will be treated with the utmost level of confidentiality. All the completed surveys will be maintained by the Graduate School of Business and Leadership, UKZN.

Rest assured that all data and information for this study will be kept in utmost anonymity and confidentiality and will only be for academic purposes. Your name will not appear

anywhere, and no one except the researcher will know about your specific answers. Furthermore, your name will not appear to be written in any thesis or publication from this study.

Competitive intelligence is a strategic tool that gathers intelligent information in the external environment. It provides market insights and opportunities on which executives make informed decisions and develop strategies to attain competitive advantage for organisations. I value your contribution to taking part in this research study. This study's results will benefit the SA long-term insurance sector to transform big data into actionable insights. Additionally, this study will assist industry leaders in making accurate and timely strategic choices, decisions, and options to keep pace with rapid changes.

If you have any questions or concerns about completing the questionnaire or about participating in this study, you may contact me or my supervisor, or the research office at the numbers listed below. The survey should take you about 25 to 30 minutes to complete.

I would like to appreciate and thank you in advance for your interest, time, and support for participating in this survey.

Researcher's name: Mpho Maluleka
E-mail: m.maluleka26@gmail.com
Mobile: +27 82 468 3384

Research Supervisor's Name: Dr B. Z. Chummun
E-mail: chummunb@ukzn.ac.za
Mobile no: + 27 64 265 8926
Office no: +27 31 260 8943

Research Office: Ms C.F. Gama (031-260 7549)

Thank you for your time and consideration in this matter.

Yours sincerely.

13.2 Appendix B: Research Questionnaire

QUESTIONNAIRE

INSTRUCTIONS

Please read each question carefully and complete the whole questionnaire.
PLEASE NOTE: This questionnaire will not be analysed on an individual basis – it is therefore important that you provide honest answers.

SECTION A - BIOGRAPHICAL DETAILS

PLEASE INDICATE YOUR RESPONSE BY TICKING THE APPROPRIATE NUMBER.

1. **Gender**

Male	1
Female	2

2. **Age**

18 - 25 Years	1
26 - 35 years	2
36 - 45 years	3
46 - 55 years	4
56 - 65	5
65+	6

3. **Marital status**

Never married	1
Married	2
Separated/Divorced	3
Not married but living with partner	4

4. Population group

White	1
Black	2
Coloured	3
Indian	4
Other	5

5. What is your position in your company?

……

SECTION B

Please indicate the extent to which you agree or disagree with each of the statements listed below by crossing (X) on the number that corresponds to your answer.

Leadership						
(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree						
L 1	Our leaders use competitive intelligence for strategic planning and decision-making.	1	2	3	4	5
L 2	Our leaders are up to date with emerging technologies and they provide the necessary resources to embed competitive intelligence in our organisation.	1	2	3	4	5
L 3	Our leaders support the use of competitive intelligence across business units.	1	2	3	4	5
L 4	Competitive intelligence is mainly used by our executive management.	1	2	3	4	5
L 5	Our leaders created a culture of sharing competitive intelligence information.	1	2	3	4	5
L 6	Our leaders use competitive intelligence to develop and formulate our corporate strategy.	1	2	3	4	5
Strategy						
(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree						
STRA1	Competitive intelligence provides our leaders with foresight to drive strategy implementation.	1	2	3	4	5
STRA 2	Competitive intelligence assists our leaders with coherent strategic goals.	1	2	3	4	5
STRA3	There is alignment between the competitive intelligence needs and our organisations strategy.	1	2	3	4	5
STRA4	Competitive intelligence is used to implement our organisations strategy.	1	2	3	4	5
STRA5	Competitive intelligence provides strategic direction for our organisation.	1	2	3	4	5
STRA 6	Competitive intelligence assists leaders in strategic planning process.	1	2	3	4	5
Structure and Process and Outcome						
(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree						
SP1	Our organisation has adequate competitive intelligence process that transforms data and information into actionable intelligence.	1	2	3	4	5
SP2	Our competitive intelligence function evaluates the reliability and accuracy of information sources.	1	2	3	4	5
SP3	Our organisation has a predefined dashboard to evaluate and monitor competitive intelligence	1	2	3	4	5
SP4	Our competitive intelligence function continually analyses and monitor competitor information to gain advantage.	1	2	3	4	5

SP5	Our competitive intelligence function is closely aligned to our business objectives.	1	2	3	4	5
SP6	Our organisation uses different methods to distribute and present market intelligence findings.	1	2	3	4	5
	Employees					
	(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree					
E1	Employees can use competitive intelligence in our operations easily	1	2	3	4	5
E2	Employees use competitive intelligence to solve complex problems for our organisation.	1	2	3	4	5
E3	Employees use competitive intelligence to perform customer analytics and insights.	1	2	3	4	5
E4	Employees use competitive intelligence to gather competitor insights for decision-making.	1	2	3	4	5
E5	Competitive intelligence is used at all levels of decision-making.	1	2	3	4	5
E6	Employees can obtain and analyze different forms of organisational information to make decisions.	1	2	3	4	5
	Competition					
	(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree					
CP1	The competition in the business environment is very intense.	1	2	3	4	5
CP2	Competitive intelligence is entrenched in our organisation to gather insights about competitor activities.	1	2	3	4	5
CP3	Our organisation entrenches competitive intelligence to cope with fierce competition.	1	2	3	4	5
CP4	Competitive intelligence assists our organisation to respond effectively to the competitive business environment.	1	2	3	4	5
CP5	Competitive intelligence prepares our organisation to deal with unpredictable elements in the market environment.	1	2	3	4	5
	Customers					
	(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree					
C1	Our organisation uses competitive intelligence to add and create value for existing and new customers.	1	2	3	4	5
C2	Our organisation gains useful customer insights from competitive intelligence to make great business decisions.	1	2	3	4	5
C3	Competitive intelligence helps our organisation to build relationships that are endured with our customers.	1	2	3	4	5
C4	Competitive intelligence provides insights about customer usage behaviour.	1	2	3	4	5
C5	Competitive intelligence increases the agility of our business to better serve our customers.	1	2	3	4	5
	Technology					
	(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree					
T 1	Our organisation has the technological infrastructure that enables dissemination of competitive intelligence.	1	2	3	4	5

T 2	Our organisation continually uses different analytical tools to gather competitive intelligence.	1	2	3	4	5
T 3	Our organisation collects competitive intelligence information from a variety of sources of information.	1	2	3	4	5
T 4	Our organisation uses software applications to create, analyse and store competitive intelligence.	1	2	3	4	5
T 5	Competitive intelligence is distributed to management timeously.	1	2	3	4	5
	Information Quality					
	(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree					
IQ1	Competitive intelligence provides accurate and timely information about competitors, customers and market opportunities.	1	2	3	4	5
IQ2	Competitive intelligence produces quality information about customers and competitors for our organisation to gain advantage.	1	2	3	4	5
IQ3	Competitive intelligence produces quality information that improves our company's image.	1	2	3	4	5
IQ4	Competitive intelligence produces quality information that is explicit to make informed decisions.	1	2	3	4	5
IQ 5	Competitive intelligence produces quality information for better decision-making across the organisation.	1	2	3	4	5
	Information credibility					
	(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree					
IC1	Competitive intelligence provides credible information for market entry development.	1	2	3	4	5
IC2	Competitive intelligence draws information that is credible from multiple sources.	1	2	3	4	5
IC3	Competitive intelligence provides reliable information to determine better ways to engage with our customers.	1	2	3	4	5
IC4	Competitive intelligence provides critical and relevant information for strategic decision making.	1	2	3	4	5
IC 5	Competitive intelligences provide relevant information for the achievement of organisational goals.	1	2	3	4	5
	Information accuracy					
	(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree					
IA1	Competitive intelligence produces accurate information that is used to confront different market opportunities and threats.	1	2	3	4	5
IA 2	Competitive intelligence provides accurate information that is used to anticipate changes in the competitive business environment.	1	2	3	4	5

IA 3	Competitive intelligence produces accurate information about the needs of our customers.	1	2	3	4	5
IA 4	Competitive intelligence distributes accurate information systematically within the organisation.	1	2	3	4	5
IA 5	Competitive intelligence provides accurate information that is used for market entry development.	1	2	3	4	5
Information Usefulness *(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree*						
IU1	Competitive intelligence provides accurate and reliable information for making quality decisions.	1	2	3	4	5
IU2	Competitive intelligence provides real-time information about current competitors and customer activities for making effective decisions.	1	2	3	4	5
IU3	Competitive intelligence provides complete information for making good business decisions.	1	2	3	4	5
IU4	Competitive intelligence provides current information on specific business needs.	1	2	3	4	5
IU 5	Competitive intelligence provides strategic information to anticipate market trends and meet the needs of customers.	1	2	3	4	5

Employee Role Clarity *(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree*						
ERC 1	Employees are personally responsible for the transfer and storage of intelligent information.	1	2	3	4	5
ERC2	Employees regularly report information they have found.	1	2	3	4	5
ERC3	Competitive intelligence has equipped employees with industry knowledge.	1	2	3	4	5
ERC4	Competitive intelligence increases employee efficiency.	1	2	3	4	5
ERC5	Employees are cognisant of the benefits created by competitive intelligence.	1	2	3	4	5

Please rate the extent to which the following are present in your company.

Information providers *(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree*						
IP 1	Competitive intelligence integrates information received from providers to make decisions that facilitates constant change.	1	2	3	4	5
IP 2	Our organisation obtains immediate competitor information from suppliers.	1	2	3	4	5
IP3	Competitive intelligence converts information from suppliers to improve employee engagement and experience.	1	2	3	4	5
IP 4	The value of information obtained from our suppliers has improved our customer's experience.	1	2	3	4	5
IP5	Competitive intelligence enriches data received from our suppliers to optimize our business processes.	1	2	3	4	5

Competitive Intelligence *(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree*						
CI1	Competitive intelligence provides market insights about the competition.	1	2	3	4	5
CI2	Competitive intelligence provides intelligence about the company's image and reputation.	1	2	3	4	5
CI3	Competitive intelligence conducts strategic early warning competition analysis.	1	2	3	4	5
CI4	Competitive intelligence scans for changes in the competitive environment.	1	2	3	4	5
CI 5	Competitive intelligence analyses and traces intelligent information for our organisation to respond effectively to change.	1	2	3	4	5

Customer Satisfaction *(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree*						
CS1	Competitive intelligence predicts customer propensity to move to competitors.	1	2	3	4	5
CS2	Competitive intelligence amplifies customer loyalty and satisfaction.	1	2	3	4	5
CS3	Competitive intelligence assisted our organisation to connect with customers from multiple touch points to retain them.	1	2	3	4	5
CS4	Competitive intelligence provides insights that improve our engagement and experience with customers.	1	2	3	4	5
CS5	Competitive intelligence increases productivity of customer-oriented resources.	1	2	3	4	5

How true are the following statements regarding your firm, over the last three years?

Organisational Performance *(1) = Strongly disagree; (2) = Disagree; (3) = Neutral; (4)= Agree; (5) = Strongly agree*						
OP1	Competitive intelligence translates organisations goals into sustainable performance.	1	2	3	4	5
OP2	Competitive intelligence is used throughout our organisation to achieve superior performance.	1	2	3	4	5
OP3	Strategic knowledge on competitor intentions increased our company's market share.	1	2	3	4	5
OP4	Competitive intelligence practices inspire organisational performance.	1	2	3	4	5
OP5	Competitive intelligence provides useful information to increase our organisations productivity and performance.	1	2	3	4	5

Thank you for your time and participation! Your feedback is very much appreciated!!

13.3 Appendix C: Informed Consent Letter

UNIVERSITY OF KWAZULU-NATAL
GRADUATE SCHOOL OF BUSINESS AND LEADERSHIP

Doctor of Business Administration (DBA) Research Project
Researcher: Mpho Maluleka (0824683384)
Supervisor: Dr B.Z. Chummun (031 260 8943)
Research Office: Ms C.F Gama (031-260 7549)

Dear Respondent,

I Mpho Maluleka, student no. 218078329 a DBA (Doctor of Business Administration), at the Graduate School of Business and Leadership, of the University of KwaZulu Natal. You cordially are invited to participate in a research project entitled "Developing a Competitive Intelligence Strategy Model for South African Life Assurance Industry".

The aim of this study is to determine whether competitive intelligence embeddedness contributes to organisational performance in the South African life assurance industry.

Through your participation I hope to develop a competitive intelligence strategy model that will be of much use to the South African life assurance industry. The results of the study are intended to be used for compilation of my theses as a requirement to achieve a DBA.

Your participation in this project is completely voluntary. You may refuse to participate or withdraw from the project at any time with no negative consequence. There will be no monetary gain from participating in this survey. Confidentiality and anonymity of records identifying you as a participant and that may lead to your traceability are not required on this survey. All the completed surveys will be maintained by the Graduate School of Business and Leadership, UKZN.

If you have any questions or concerns about completing the questionnaire or about participating in this study, you may contact me or my supervisor at the numbers listed above.

The survey should take you about 30 minutes to complete. I would like to appreciate and thank you in advance for your interest, time, and support for participating on this survey.

Sincerely

_____ _____

Mpho Maluleka Date
(Investigator's signature)

NB: *Participant's Copy.*

UNIVERSITY OF KWAZULU-NATAL
GRADUATE SCHOOL OF BUSINESS AND LEADERSHIP

Master of Business Administration (MBA) Research Project
Researcher: Mpho Maluleka (0824683384)
Supervisor: Dr B.Z. Chummun (031 260 8943)
Research Office: Ms C.F Gama (031-260 7549)

CONSENT

I…… (full names of participant) hereby confirm that I understand the contents of this document and the nature of the research project, and I consent to participating in the research project.

I understand that I am at liberty to withdraw from the project at any time, should I desire to do so.

Signature of participant: _____ Date: _____

NB: *Researcher's Copy*

13.4 Appendix D: Gatekeeper Letters

13.4.1 Appendix D 1: Letter of Consent from PPS

FINANCIAL ADVISORY

6 Anerley Road, Parktown, Johannesburg, 2193
P O Box 1089, Houghton, 2041
Tel: +27 (0) 86 012 3777
lifeplan@pps.co.za | www.pps.co.za

25 April 2019

To,

Mpho Maluleka,
114 Ninth Avenue, Fairlands, Randburg, 2170
Researcher and Student of the University of KwaZulu Natal

And

Dr Bibi Chummun,
Research Supervisor of the University of KwaZulu Natal

Letter of Consent to Conduct Research as PPS

The following letter serves to notify those concerned that PPS hereby grants Mr. Mpho Maluleka with student number: 218078329, a Doctoral student from the University of KwaZulu Natal, permission to conduct the required doctoral research project at PPS, with the title of; "Developing a Competitive Intelligence Strategy Model for South African Life Assurance".

The contact for the above at PPS will be Mzwandile Mtshali who is the PPS Executive for Advisory Services and Enablement. The executive's contact details are as follows:

Direct Line: 27+ (0)11 644 4613
Mobile: 27 + (0)82 920 0266
Email: Mmtshali@pps.co.za

Should you have any queries regarding this consent please contact the Executive directly.

[redacted]

Mzwandile Mtshali
Executive: Advisory Services and Enablement

13.4.2 Appendix D 2: Letter of Consent from Liberty Group

LIBERTY

LIBERTY GROUP LIMITED

Liberty Centre, 1 Ameshoff Street, Braamfontein 2001
PO Box 10499, Johannesburg 2000
t 0860 456 789 f 0866 880 713
e info@liberty.co.za w www.liberty.co.za

29 May 2019

To:
Mpho Maluleka
114 Ninth Avenue, Fairlands, Randburg, 2170
Researcher and Student of the University of KwaZulu Natal
&
Dr Bibi Chummun
Research Supervisor of the University of KwaZulu Natal

RE: Consent to Conduct a Doctoral Research Project at Liberty Group

This letter serves to notify those concerned that Liberty Group hereby grants Mr. Mpho Maluleka, student number, 218078329, permission to conduct the required doctoral research project at Liberty Group, titled, "Developing a Competitive Intelligence Strategy Model for South African Life Assurance".

We hereby grant this permission subject to the proviso that participation in this survey is entirely voluntary and there are no known or anticipated risks to participation to this study. All data and information for this study will be kept in utmost confidentiality and would be strictly used for academic purposes only. The names of the respondents and the company will not be written in any thesis or publication from this study unless agreed to with Liberty Group.

The contact person for the above approval at Liberty Group is:
Pumeza Bam
Executive: Human Capital
Pumeza.bam@liberty.co.za
011 408 4088

Yours Sincerely,

Pumeza Bam

[redacted]

ADVISE INSURE INVEST

13.4.3 Appendix D 3: Letter of Consent from MMI Holdings

momentum

9 May 2019

Mpho Maluleka,
114 Ninth Avenue, Fairlands, Randburg, 2170
Researcher and Student of the University of KwaZulu Natal
And
Dr Bibi Chummun,
Research Supervisor of the University of KwaZulu Natal

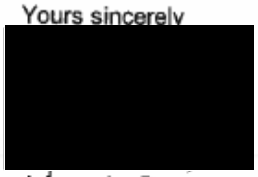
Letter of Consent to Conduct a Doctoral Research Project at MMI Holdings

This letter serves to notify those concerned that MMI Holdings hereby grants Mr. Mpho Maluleka, student number: 218078329, a Doctoral student from the University of KwaZulu Natal, permission to conduct the required doctoral research project at MMI Holdings, with the title of; "Developing a Competitive Intelligence Strategy Model for South African Life Assurance".

We hereby grant this permission subject to the proviso that participation in this survey is entirely voluntary and there are no known or anticipated risks to participation to this study. All data and information for this study will be kept in utmost confidentiality and would be strictly used for academic purposes only. The names of the respondents and the company will not be written in any thesis or publication from this study unless agreed to with MMI Holdings.

The contact person for the above request at MMI Holdings is Johann Le Roux and his contact details are: johann.leroux@momentum.co.za, telephone number 012 673 7326.

Yours sincerely



Johann Le Roux
CEO : Momentum Life

13.4.4 Appendix D 4: Letter of Consent from Sanlam

Sanlam

114 Ninth Avenue
Fairlands
Randburg
2170
29 March 2019

C/O Dr Bibi Chummun

To whom it may concern

With this letter we grant Mr. Mpho Maluleka (student no: 218078329), a doctoral student from the University of KwaZulu Natal (UKZN) permission to conduct his doctoral research project at Sanlam, with the title: "Developing a Competitive Intelligence Strategy Model for South African Life Assurance Industry".

Kind regards

[redacted]

Jean Dommisse
Head: Client and Market Insights
Sanlam Personal Finance

13.5 Appendix E: Editors Certificate

Writing Splendour Services & Consultancy
(A Subsidiary of Oaks- Executive Consult)
L13b, Off Boardwalk Inkwazi Shopping Centre, Richards Bay, South Africa.
Tel: +27639127312 Email:myfreelancewritingbiz@gmail.com
writingsplendour247@gmail.com
Website: www.writingsplendour.simplesite.com
Income Tax Number: 1064112236

January 27, 2022

To Whom It May Concern

EDITING AND PROOFREADING OF A DOCTORAL DEGREE DISSERTATION

This is to certify that I, (Olumuyiwa A. Kehinde) edited and proofread a doctoral degree dissertation by **Mpho Lawrence Maluleka** titled: ***DEVELOPING A COMPETITIVE INTELLIGENCE STRATEGY MODEL FOR SOUTH AFRICAN LIFE ASSURANCE INDUSTRY.***

Specifically, I commented on the grammatical anomalies in MS Word Track Changes and review mode by the insertion of comment balloons before I returned the document to him. Corrections were made in respect of grammar, punctuation, spelling, syntax, tense and language usage, sense and flow, syntactic and semantic cohesion, clarity of expressions, appropriate use of reference style, typing format and layout.

I have completed a PhD programme, and I have a Master's degree in English, Bachelor of Arts in English Studies, Diploma in Communication Science, and Teachers' Grade II Certificate. I have been teaching Advanced English Courses for the past 9 years. I also teach English for IELTS and TOEFL examinations. Furthermore, I have been regularly editing and proofreading academic, research dissertations, theses, articles, and other documents for the past 6 years in different disciplines for publishing /editing firms, schools and individuals.

I trust that the document will prove acceptable in terms of editing, formatting, and proofreading criteria.

Thank you.

Yours faithfully,

[redacted]

Mr O.A. Kehinde

13.6 Appendix F: Ethical Clearance

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

22 August 2019

Mr Mpho Lawrence Maluleka (218078329)
Grad School Of Bus &Leadership
Westville Campus

Dear Mr Maluleka,

Protocol reference number: HSSREC/00000221/2019
Project title: Developing a Competitive Intelligence Strategy Model for South African Life Assurance Industry

Full Approval – Expedited Application

This letter serves to notify you that your application received on 15 July 2019 in connection with the above, was reviewed by the Humanities and Social Sciences Research Ethics Committee (HSSREC) and the protocol has been granted **FULL APPROVAL**

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number. PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

This approval is valid for one year from 22 August 2019.
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

Yours sincerely,

[redacted]

Professor Urmilla Bob
University Dean of Research

/dd