

The Perceived Impact of Artificial Intelligence on Operations Performance in the South African Life Insurance Industry

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

Johannesburg, 2021

ABSTRACT

Organisations are increasingly implementing AI applications in their operations in order to stay competitive. The Covid-19 pandemic has further fuelled the implementations of AI technologies. However, do these applications improve the operation's performance of an organisation?

The study investigates how managers and employees that have implemented AI technologies within life insurance organisations perceive AI to have impacted their operations performance. Operations performance measures used by the study are cost, quality, speed, flexibility, and dependability.

A qualitative methodology was undertaken by the study, using in-depth interviews that were made up of open-ended questions. The participants that contributed to the study were selected based on their profile and experience with AI technologies and in the life insurance industry.

The findings of the study show that AI technologies generally improved operations performance. However, it must be noted that AI implementations come at a very high cost. Therefore, using cost savings as a sole use case driver is discouraged. Also, AI must not be implemented to improve inefficient business processes. Lastly, the quality of data to be used by the AI application is essential to the success of the project.

In conclusion, managers and employees that have implemented and/or used AI technologies in the life insurance industry perceive AI to have improved operations performance of their organisations. An improved operations performance helps the organisation to stay competitive among its peers.

KEYWORDS

Artificial intelligence; performance measures; performance objectives; operations performance; life insurance

DECLARATION

I, Thamsanqa Kunene, declare that this research report is my own work except where it is indicated in the references and acknowledgments. This research report is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. This research report has not been submitted before for any degree or examination in this or any other university.

Name: Thamsanqa M. Kunene

Signature:

A handwritten signature in black ink, appearing to read 'T. Kunene', written in a cursive style.

Signed at: Fourways, Johannesburg

On the 31st day of March 2022

DEDICATION

I dedicate this work firstly to myself for persevering to the finish line. To my parents who are a pillar of my strength and have encouraged me to embark on this journey to complete my master's degree. Lastly, to my family, friends and colleagues that have supported me throughout this journey.

ACKNOWLEDGEMENTS

I would like to thank all the people that contributed to contributed to the successful completion of this research report.

A special thanks to my supervisor, Dr Erasmus Kofi Appiah for the guidance in this academic milestone.

I would like to acknowledge and thank the Wits Business School for giving me the platform to undertake this research study. It has been a learning and empowering journey.

I would also like to thank all the people that took their time out of their diaries to participate in this study. This work would have not been possible without their input.

I would like to thank all the writers that were cited in this research study. Their prior studies were a great input into this research study. Lastly, I would like to thank the MMDB class of 2020, especially my syndicate group that made the learning experience enjoyable amidst the challenges we were facing.

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LIST OF ACRONYMS

AI – Artificial intelligence

CRM – Customer relationship management

DARPA – Defense Advanced Research Projects Agency

ERP – Enterprise resource planning

IT – Information technology

RPA – Robotic process automation

SA – South Africa

CHAPTER 1. INTRODUCTION

1.1 Purpose of the study

A company must be innovative to improve or maintain its level of performance (Hernández, Jiménez, & Martín, 2008)). Technology innovations, such as Artificial Intelligence (AI), can lead to better quality, higher efficiency, and improved outcomes than human experts (Haefner, Wincent, Paridacde, & Gassmanna, 2021). Artificial intelligence-driven processes exhibit human intelligence and are capable of intuitive decision-making abilities, can perform tasks such as recognition of complicated models, integrating critical material, drawing inferences/decisions and forecasting (Elapanda, Kumar, & Rao, 2020). Artificial Intelligence (AI) can be described as the imitation of human intelligence in machines like robots or computers that are automated to simulate cognitive functions that reflect problem solving abilities of humans (Lee & Yoon, 2021).

The study investigates how AI is perceived by managers and employees that have used AI applications in their organisations to enhance the organisation's operations performance by using cost, quality, speed, flexibility, and dependability as operations performance objectives. Further, for the purpose of this study, life insurance will be the primary unit of analysis. This is important because both AI and operations performance can be used as a competitive advantage by insurance organisations. High operations performance can lead the organisation to satisfy its customers and contribute to its competitiveness in different ways.

1.2 Background of the study

The life insurance industry forms an important component of the SA economy and given the global pandemic, innovations that can support the operations performance and add to competitiveness, are required – in the virtual or in the physical office space (KPMG, 2019).

Insurance companies have indicated that they are behind the curve in operations efficiency with a lack of process standards and strategic vision as main inhibitors (KPMG, 2019). Also, customer expectations in the life insurance industry are changing due to rapid digital advancement. Lockdowns and working from home due to Covid-19 have also accelerated digitalisation and shifted digital interaction expectations to be normal (McKinsey & Company, 2020). Customer expectations are also shaped by experiences in other industries where interactions, features and content are much better (PwC, 2017). Customers today, prefer using social media to get feedback on products and services. They are also more informed about product alternatives and prices, which determines their buying behaviour (PwC, 2017). These changes mean a business must be able to support self-service operations and use technology by being virtual.

Life insurance is described as a pool of risks that aim to provide peace of mind and support to customers in times of need and distress (PwC South Africa, 2020). This is done through the following:

- Protecting customers from the loss of income due to an illness, disability, or death of a family member
- Help customers provide for expenses that can arise in these circumstances.
- Assisting customers to build and managing their wealth.

The life insurance industry is among the oldest industries in South Africa (Verhoef, 2012). Companies such as Sanlam, Discovery, Old Mutual, Liberty Holdings and Momentum Metropolitan Holdings Limited are leaders in the industry. The Financial Services Conduct Authority had registered 65 primary life insurers, five life cell captives, one life micro insurer, five composite reinsurers, and two life reinsurers in 2020 (Research and Markets, 2021). There were over 43 million individual business policies and almost 87,000 group business policies at the end of the year 2020 (ASISA, 2020). This is therefore a big and highly competitive industry.

To stay competitive or lead the competition, a life insurance company must manage operations resources efficiently. Operations resources are responsible

for converting inputs using the input-transformation-output approach (Slack, Brandon-Jones, Johnston, Singh, & Phihlela, 2017). Operations performance can be measured in various ways. This research study uses the five performance objectives mentioned by Slack et al. (2017) which are: cost, quality, speed, dependability and flexibility.

These performance objectives are all relevant to maintaining a competitive edge in the insurance industry. For instance, Kumar (Kumar, Srivastava, & Bisht, 2019) states that there is an opportunity cost in getting through to prospective customers promptly and high costing claims impact negatively on the profitability of the organisation (cost), providing the right products that meet customer requirements (quality), dealing with claims as quickly as possible (speed), being efficient by decreasing number of false or fraudulent claims and the extent of large data being processed manually rendering operations slow and bulky.

The research study will be based on the industry leaders in life insurance. Market leaders are chosen for this study because they reflect the industry.

1.3 Research problem and research question

The rise of AI has become a critical driver for change in many industries (Agrawal, Goldfarb, & Gans, 2016). This rise is driven by the huge advances in technology, computer power, big data technologies, changes in customer expectations and global connectivity of people and machines (Hall, 2017).

AI applications can benefit organisations by improving the organisation's performance and creating a competitive advantage (Nadimpalli, 2017). AI can help organisations to cut costs and improve the quality of their services, productivity, coordination, and efficiencies (Davenport, 2018). AI can also help with improving decision making, ecosystems, and customer experience (Gartner, 2017a.). Also, AI can lead to the introduction of new revenue streams, improved loss predictions and changes to the business model from a loss compensation approach towards loss prediction and prevention (Eling, Nuessle, & Staubli, 2021).

Life insurance organisations have not been at the forefront in adopting AI technologies and therefore enjoy the benefits. The covid-19 pandemic together with a series of lockdowns and changing customer preferences towards digital platforms has accelerated the adoption of digital technologies including AI.

However, there is literature shortfall regarding the perception of AI in the life insurance industry. Hence the importance to conduct a qualitative study to gain in-depth understanding of how AI applications are perceived to enhance operations performance by managers and employees in the insurance industry.

1.4 Research objectives

This study focuses on exploring and understanding how managers that have implemented AI perceive AI applications to have enhanced operations performance.

The research objectives are to:

1. Investigate the level of AI awareness in the life insurance industry
2. Investigate the state of AI implementations in the life insurance industry.
3. Investigate the type of AI Applications that have been implemented within life insurance organisations
4. Investigate the factors driving AI technologies implementation
5. Investigate how AI is perceived to have improved operations performance of selected life insurance organisations using the five operations objectives

Research Questions

1. What is the level of awareness of AI in the life insurance industry?
2. What is the state of AI applications in the life insurance industry?
3. What are the types of AI applications implemented within the life insurance industry?
4. What are the factors driving AI implementations?

5. Is AI perceived to have improved the operations performance of the selected life insurance organisations based on the five operations objectives?

1.5 Significance of the study

The introduction of AI in business is new. In an increasingly technology-driven business environment, of which the life insurance industry is but one, the outcomes of the study will benefit managers in the life insurance industry with views on how AI has improved operations performance and led to better customer service and organisation success. Although the study will be conducted in a selected life insurance environment, the outcomes could be used in similar services settings to enhance competitiveness through better customer experience as brought about by operations improvements.

The study will further benefit researchers in the field as this adds theory to using AI to enhance operations performance in a services environment.

This empirical research will be based on online one-on-one interviews with operations managers, through open-ended questions to gather data on the enhanced operations performance after the implementation of AI. The data gathered will be analysed to confirm if AI implementation does enhance operations performance. The selection of people to participate in the study will be done based on their experience of implementing AI in a life insurance setting. The methodology framework will explore each operations performance objective with the participants to determine how AI implementation has enhanced it.

1.6 Delimitations of the study

Insurance is categorised into two, namely life insurance and non-life insurance. Life insurance includes life protection and investment policies. Whereas non-life insurance includes policies that cover property, auto, health, accidents, travel, credit and mortgages. The study focuses on life protection insurance only, therefore life investment and non-life insurance are not in the scope of the study.

There are many ways to measure operations performance. This study focuses on using cost, quality, speed, dependability, and flexibility as measures of operations performance within the selected life insurance environment. Other ways of measuring operations performance are not in the scope of the research study.

1.7 Study Outline

Chapter 2 covers the literature review. It kicks off with the definitions of AI and operations management, then delves deeper into the literature review. The literature review covers the AI history, AI types, AI applications, operations performance including the performance objectives and some examples of how AI has been used.

Chapter 3 covers the research methodology. It begins by explaining the qualitative research approach taken for this study. Then it moves to explain the research design which is based on a case study approach and with one-on-one interviews as a form of data collection method. The chapter then moves on to the sampling method for the participants, the research instrument follows thereafter and the procedure regarding data collection. Then, the data analysis together with the data interpretation, limitations of the research study, transferability & dependability and lastly the ethical considerations are discussed.

The consistency table is then covered consisting of the research question, proposition, data collection and lastly, the data analysis method.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

The literature review investigates how AI can be used by operations management to improve operations performance. First, the definition of AI and operations performance concepts is undertaken. Then the literature review covers the AI historical background, types of AI and AI applications in the insurance industry. Then operations management, operations performance, and the impact of AI in the life insurance industry are covered. Lastly, the research proposition is stated.

2.2 Definitions of concepts

2.2.1 AI

AI is the imitation of human intelligence in machines like robots or computers that are automated to simulate cognitive functions that reflect problem solving abilities of humans (Lee & Yoon, 2021). Characteristics of true AI are based on the ability to accurately interpret data, learn from the data and apply learnings to achieve a certain outcome or goal (Haenlein & Kaplan, 2019). Today, AI can be found in many applications we use daily. Examples include spam identification on emails, recommendations on items one can buy online, and virtual assistants such as Google assistant or Siri.

Examples of AI in life insurance include (Kaushik, Bhardwaj, Dwivedi, & Singh, 2022):

- Using chatbots to answer customer queries regarding insurance product features and claims.
- Using AI to learn from previous experience to reduce claim processing times and detect fraudulent claims.
- Using an individual's data to personalise their insurance policy.
- Using information from AI technologies such as wearables to underwrite an individual

2.2.2 Operations Performance

Operations management plays a critical role in an organisation's success (Niall, 2012). The operations function is judged by the way it performs (Slack, Brandon-Jones, Johnston, Singh, & Phihlela, 2017). Schroeder et al. (2011) define operations performance as the level of achievement of the organisation priorities. The measurement of performance is explained by Neely et al. (2005) as "the procedure of evaluating the efficiency and effectiveness of action." Therefore, operations performance measures whether the organisation has achieved its intended operations strategy.

2.3 Technology Adoption in the Insurance Industry

Diffusion of innovation relates to the communication and filtering of innovation through specific mediums among members of a social system (Rogers, 2003). The use of smart phones already allows customers to contact any insurance service provider with just a touch. This presents insurers with opportunities to create new touch points with clients, access new clients and offer improved customer experience using new technologies (Nguyen, 2019). An Accenture study found that companies in South Africa are adopting newer technologies such as AI, cloud, blockchain and agile methodologies to meet customer demand and remain competitive (Accenture, 2020). Covid-19 has accelerated the move to online channels and business has responded accordingly with digital offerings (McKinsey & Company, 2020).

2.4 Literature Review

2.4.1 *AI Historical Perspective*

AI has existed for much longer than understood, as it can be traced back to ancient Greece (Dennehy, 2020). The concept of intelligent or thinking machines was first introduced in 1950, by Alan Turing in what is famously known as the Turing Test (Bringsjord & Govindarajulu, 2018). Alan Turing was a British mathematician that took interest in intelligence of machines after developing a code breaking machine called The Bombe. This machine is considered as the first working electro-mechanical computer to successfully decipher the Enigma code used by the German army in the second world war. This task had been impossible to achieve by human mathematicians at the time. In 1950, Alan Turing wrote an article called Computing machinery and intelligence, which described how to create intelligent machines and how to test their intelligence. The Turing Test state that, if a human is interacting with another human and a machine and cannot tell the difference between the human and the machine, then that machine can be categorised as intelligent. The Turing Test still forms the basis of identifying intelligence in machines *even today* (Haenlein & Kaplan, 2019).

The AI terminology was coined in 1956 at a DARPA-sponsored conference at Dartmouth College, New Hampshire hosted by Marvin Minsky and John McCarthy (McCorduck, 2004), whereby AI was defined as “the science and engineering of creating intelligent machines”. This occasion was also referred to as the birth of AI (Russel & Norvig, 2020) and marks the beginning of the AI spring. The main objective of this occasion was to bring together researchers from different fields to create a new area of research to build machines that can simulate human intelligence.

After the Dartmouth conference, the AI field saw huge success for nearly 2 decades. One of the success examples is the ELIZA computer program that was created by Joseph Weizenbaum between 1964 and 1966. This program could simulate a conversation with a human using natural language processing. Another success example is the General Problem Solver program that could

solve simple puzzles such as the Towers of Hanoi. These success stories led to more funding of AI research and projects. The huge success in AI led to Minsky making a bold statement in 1970, that machines with the intelligence of an average man will be developed within 3 to 8 years. However, this bold proclamation was never achieved but it gives us an indication of the early success of AI.

Three years later after Minsky's proclamation in 1973, the US congress criticised the huge amount spent on AI research. On the very same year, the British Science Research Council through James Lighthill also criticised the AI research outlook. Lighthill criticised the intelligent machines' ability to simulate common sense and confining intelligent machines to only achieving levels of "experienced amateur" only in games such as chess. This criticism was followed by the withdrawal of AI research support by the British government from all universities except for Essex, Sussex and Edinburg. This action was adopted by the US which also cut support for AI research. These actions marked the beginning of the AI winter.

In 1980, the Japanese government began funding AI research, and this led to DARPA also increasing its funding for AI research. However, not much progress was achieved in the years that followed.

One of the reasons for the slow progress in AI can be traced back to the initial success of AI through ELIZA and the General Problem Solver. These systems are expert systems and are based on structured "if-then" rules. Expert systems are excellent in structured, formal areas. An example is IBM's Deep Blue which is a program for playing chess. Deep Blue defeated Gary Kasparov a world champion by processing 200 million possible moves per second while projecting 20 moves ahead through tree search method.

However, expert systems fail spectacularly in circumstances that lack a formal structure such as facial recognition or differentiating between a dog and a cake. Such tasks require the machine to interpret data accurately, learn from the data and apply the learnings to reach a goal. These are the true characteristics of AI,

which expert systems lack and therefore making expert systems to be seen as not true AI.

Statistical methods to achieve true AI date back to the 1940s with the Hebbian Learning theory that replicated the neurons process in the human brain. This theory was introduced by Donald Hebb who was a Canadian psychologist. This led to the beginning of research in artificial neural networks. Progress in this area of research however was stalled in 1969 after the discovery that computers lack the processing power for this kind of work.

In 2015, artificial neural networks re-emerged as deep learning through Alpha Go developed by Google. Alpha Go defeated a world champion in a board game called Go, that is way more complicated than chess due to 361 possible moves instead of 20 in chess. This feat was never seen as a possibility due to the complexity of Go. Presently, artificial neural networks and deep learning form the foundation of most AI applications such as, speech recognition algorithms, image recognition algorithms and self-driving cars (Haenlein & Kaplan, 2019)

The below diagram shows the AI timeline (Zyl & Klein, 2020).

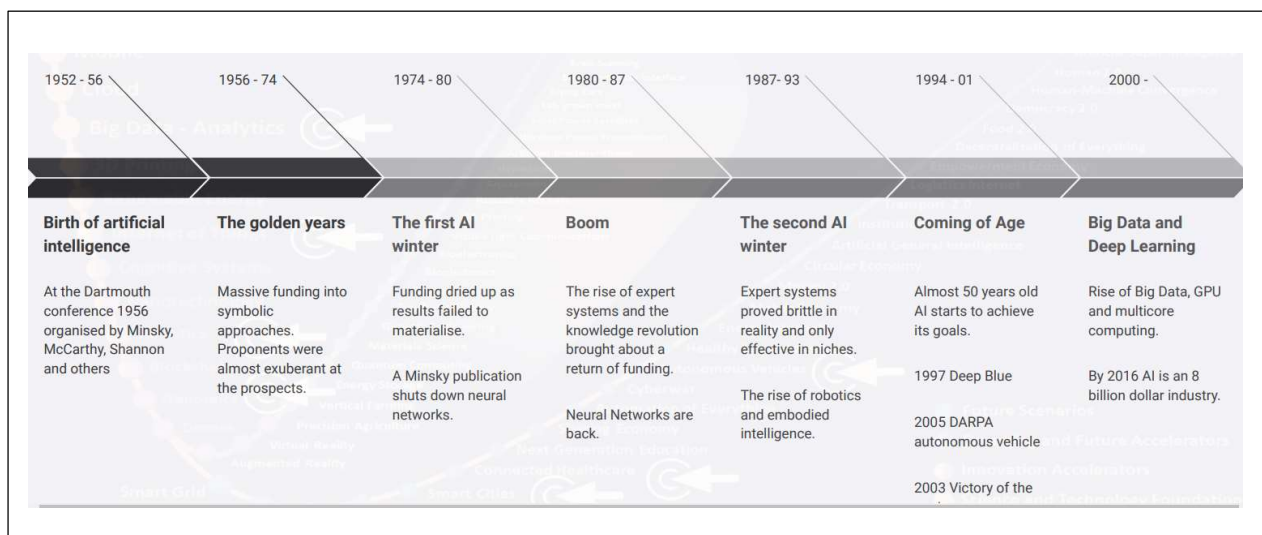


Figure 1: The Artificial Intelligence Timeline (Source: WBS MMDB 2020: AI Slides page 15)

The above historical perspective of AI shows that AI will be more prevalent in our lives and business will be able to use the available AI tools to enhance decision making. This means that life insurance organisations that want to improve the

operations performance of their organisations will continue to have access to AI tools into the future and therefore continuously stay ahead of its competitors.

2.4.2 *Types of AI*

At a high level, AI can be categorised into two types: narrow AI and general AI. Narrow AI includes intelligent machines that were trained to execute specific tasks without being explicitly programmed to do so (Heath, 2019). Most of the existing and complicated AI applications fall in this category. Examples include recommendation engines, vision-recognition applications on self-driving cars and speech & language recognition on Siri virtual assistant. They are referred to as narrow AI because they were taught to do specific tasks. General AI on the other hand can learn, understand and function exactly like humans (Joshi, 2019). They have adaptable intelligence found in humans and can execute completely different set of tasks from hairdressing to preparing spreadsheets to reasoning on a wide variety of topics. General AI can only be seen on movies such as The Terminator and does not exist yet. It is not known when this type of AI will be a reality.

AI can also be classified into functional, analytical, interactive, visual, and textual AI (Saker, 2022). 1) Analytical AI involves identifying, interpreting, and communicating data patterns. Its focus is on unearthing new insights, patterns, and relationships. Analytical AI is at the core of insights and recommendations. 2) Functional AI shares some similarities with analytical AI as it also investigates finding patterns and relationships in data. The differentiating factor is that functional AI performs actions instead of recommendations. 3) Interactive AI enables automated and collaborative communication through smart personal assistants and chatbots. 4) Visual AI enables recognition, classification, and the conversion of images and videos into insights. 5) Textual AI includes textual analytics and natural language processing which enables business to use text recognition, speech-to-text conversion and content generation. An example is using textual AI to answer customer queries.

2.4.3 Business Needs supported by AI

Business operations must understand the different types of AI and the tasks they can perform. Generally, AI can support three business needs, and these are business process automation, data insights, and customer engagement (Davenport & Ronanki, 2018).

a. Process Automation

Process automation involves automating tasks such as back-office administration and financial activities using robotic process automation (RPA) technologies. RPA involves using technology to imitate a worker by automating organised tasks and activities in a speedy and cost-efficient manner (Slaby & Fersht, 2012). RPA does not involve a physical robot but involves a software program that carries out mundane operational tasks and activities performed by employees (Lacity & Willcocks, 2016). RPA can automate business processes that are rules-based involving standardised tasks, organised data, and predetermined outcomes, such as moving data from different platforms like email and spreadsheets to other platforms such as ERP and CRM. Some of the RPA applications automate tasks such as validating insurance premiums, generating customer billing for collections, paying insurance claims, updating employee records, and communicating to customers among others (Lacity & Willcocks, 2016). Business processes suited for RPA must have the following characteristics suggested by (Fung, 2014):

- Low cognitive tasks that do not require personalised judgment, interpretation or creativity skills.
- High volume tasks that are frequently performed.
- Access to multiple systems to perform the job of one process.
- Limited exception handling tasks and activities –that are highly standardised with limited or no exceptions.
- Tasks that are prone to human error.

However, it must be noted that RPA does with some disadvantages:

- Implementing and maintaining an RPA software comes at a cost.

- End-user must possess technical skills to resolve complex issues.
- The organisation must adapt to changes brought by the new RPA software.
- RPA brings fear to employees as it is thought to replace humans.
- RPA comes with a new risk type of data breach through cyber security

b. Cognitive Insight

This involves getting insights from huge volumes of data on customers and transactions, that include numbers, text, voice, image, or facial expression and interpreting their meaning (Davenport, Guha, Grewal, & Bressgott, 2019). Cognitive insight applications can be used to:

- Predict or recommend what a customer can buy.
- Detect insurance claims fraud or credit card fraud before it happens.
- Provide insurers with an accurate and detailed actuarial model.
- Provide real time targeted digital advertising.

c. Cognitive Engagement

This involves interacting with customers via chatbots and intelligent agents that use natural language processing (Davenport, Guha, Grewal, & Bressgott, 2019). According to Davenport (2019), the benefits of implementing AI chatbots and intelligent agents include:

- 24/7 customer service in the customer's natural language.
- Lower error rates.
- Creating more time for agents to spend on complex activities.
- Ability to scale up or down based on demand.

The research focuses only on these business needs due to the time constraints.

2.4.4 AI Applications in Insurance

The below table shows how the AI applications have been implemented in the insurance industry based on an assessment conducted by Eling. et al. (2021). These applications are classified according to the application areas:

Language or text conversion:

- Voice recognition and natural language generation
- Text analytics and natural language processing
- Sentiment detection

Trends, patterns, and preferences recognition:

- Pattern, trends, and anomaly detection in data sets
- Predictive analytics
- Recommendation engine

Content-based processing of information and data-driven decision making:

- Image and video analysis
- Facial recognition and biometrics
- Automatic decision making

Table 1: AI Applications in Insurance

Application	Explanation	Implementation
Language or text conversion		
Voice recognition and natural language generation	Identifying, understanding, and interpreting phrases or words. Generating information into a natural language from verbal and written data sets.	Insurers such as Lemonade, AXA, Allianz launched chatbots that respond to requests from customers. ABLE virtual sales assistant was implemented by Allstate to support sales agents in quoting.

Text analytics and natural language processing	Understand, classify, and interpret text into computer-readable data sets.	IBM Watson uses natural language processing to sort customer mails leading to improved customer service
Sentiment detection	Detect and analyse emotions in words that have been written or spoken	Some insurance companies are experimenting with sentiment detection to increase customer satisfaction and retention
Trends, patterns, and preferences recognition		
Pattern and anomaly detection	Detecting patterns in unstructured data sets and generating a conclusion	Insurers are implementing pattern and anomaly detection to identify fraudulent claims. Examples are Ping An, Allianz, AXA and Aegon
Predictive analytics	Using big data analysis to predict future outcomes	Insurers are applying predictive data analytics and developing personalised insurance products
Recommendation engine	Interpreting data and recommending data-driven actions	Recommendation engines that help consultants to take advantage of cross-selling and up-selling opportunities
Content-based processing of information and data-driven decision making		
Image and video analysis	Analysis and interpretation of people or objects.	Risk assessment and underwriting processes by analysing uploaded pictures.
Facial recognition and biometrics	Interpret biological attributes such as the structure of one's face.	Using biometrics authorisation to identify users.

Automated decision making	AI systems that rely on automatic application of rules to decide	Using robo-advisors.
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Source: (Eling, Nuessle, & Staubli, 2021) page 11 - 12

2.4.5 The Impact of AI Applications to the Operations Performance of Selected Insurance Organisations

According to Eling and Lehmann (2018), AI has impacted insurance in three broad ways.

The first impact is how AI has changed the way insurance companies interact with customers. Traditionally customers had to interact with insurance agents to enquire, purchase or perform servicing on their insurance products. The internet has made insurance product information and services easily available to potential customers through chatbots without human interaction. This means insurance agents can now be used elsewhere to add value as chatbots have taken some of their tasks. Customers also benefit through customer service and product information that is always available. AI can furthermore be used in risk reduction and prevention such as proactively reaching to a customer in a high-risk situation. This allows insurance companies to move from a 'detect and repair' to a 'predict and prevent' approach (Kelley, Fontanetta, Heintzman, & Pereira, 2018). Thus, allowing insurance companies to prevent losses than to compensate losses (Schmidt, 2018).

The second impact is the automation of business processes using big data and AI. Automation will drive benefits such as cost savings, high accuracy of administrative tasks through the elimination of human error on repetitive tasks, employees will spend more time on value-adding activities and improvement in turn-around times (speed) for processes such as claims pay-out.

Lastly, AI will invent new markets and risks and lead to certain traditional markets to disappear (Schmidt, 2018).

The below table shows the impact brought by AI to the performance of insurance companies that implemented AI applications.

Table 2: The Impact of AI to the Performance of some Insurance Companies

Function	Impact of AI to Performance of Some Insurance Companies
Marketing	Predictive data analytics and pattern detection: • Increased customer lifetime value prediction • Enhanced personalisation of customer communication Recommendation engine: • Advanced insights on customer taste based on buying behaviour leading to cross-selling opportunities and product recommendations • Development of advanced marketing strategies to improve customer experience
Product Development	Predictive analytics, pattern, and anomaly detection: • Advanced insights on prompt big data analysis enable insurance companies to develop innovative products, such as usage-based insurance • Introduction of complementary services such as early detection of risks and prevention allows insurance companies to add new revenue streams and risk coverage Predictive analytics, image, and video analysis: • Development of new markets and ecosystems such as real-time health
Sales and Distribution	Natural language generation, predictive analytics, and recommendation engine:

	- Using virtual assistants to support sales agents improve consultations with customers and make customised product recommendations Voice recognition and natural language generation: - Using chatbots to provide automated advice on products and facilitate sales
Underwriting and pricing	Image analysis, natural language processing and pattern detection: - Automated underwriting processes that allow for the generation of accurate quotes within minutes Predictive analytics: - Real-time data analysis from customer IoT devices allow for ongoing premium pricing for usage-based insurance plans
Customer Servicing	Voice recognition and natural language processing and generation: - Use of chatbots to answer customer queries (written or verbal) Predictive analytics: - Proactive and regular customer engagement Recommendation engines: - Offering product recommendations from a customer servicing perspective
Claims	Natural language processing, image analysis and anomaly detection: - Accurate claims pay out and quicker turnaround times due to automated claims processes - Improved fraud detection

Source: (Eling & Lehmann , 2018) page 14-16.

2.4.6 Operations Management

Operations management dates to the end of the 19th century in the manufacturing industry which was characterised by very low product variety and process variability (Sprague, 2007). Standardisation and specialisation principles were used to achieve superior performance. In the beginning of the 20th century, the service industry made up of insurance companies, banks, accounting firms and hospitals implemented the operations management principles from the manufacturing industry to achieve superior performance (Chase & Apte, 2007).

The Association for Operations Management has described operations management as the “subject area that focuses on the essential planning, scheduling, using, and the control of a manufacturing or service firm and their operations”. Jabbour & Jabbour (2013) further define operations management as the responsibility of ensuring the efficiency and effectiveness of the transformation process to delivers products and services that satisfy the market needs. Slack et al. (2017) state that managing operations resources efficiently will enable the organisation to compete by being able to respond to customer needs and through building capabilities that will help it stay ahead of competition.

2.4.7 Operations Performance

Operations can be gauged by the way they perform (Slack, Brandon-Jones, Johnston, Singh, & Phihlela, 2017). Operations performance can be measured in various ways. One way to measure performance is through financial indicators like return on equity (i.e. ROE), return on investment (i.e. ROI), (Rai, Patnayakuni, & Patnayakuni, 1997) and revenue (Rai, Patnayakuni, & Seth, 2006). These indicators show the organisation’s ability to be profitable. Another way is to use efficiency-related indicators that can investigate the impact of operations efficiency such as cost reduction, productivity, and expenses (Liang, You, & Liu, 2010). Other indicators include customer satisfaction, market share and value addition. Boyer & Lewis (2002) suggest that there is a consensus to measure performance by using cost, quality, speed, dependability, and flexibility. The research study will focus on these performance measures.

Various authors have contributed to the definitions of these performance measures. The study has adapted definitions from Musyoka (2016):

- Cost refers to the ability to minimise costs while still allowing for a return to the organisation. An organisation that can successfully lower its operations cost achieves a cost advantage.
- Quality refers to the ability of the operation to do things right, such as life insurance products and services that are to specification and error free.
- Speed refers to the operation's ability of doing things fast and minimising the time between a customer making a request and the time they receive the product or service. This can involve quick quotation, underwriting, servicing, and claims.
- Dependability describes the operation's capability to deliver insurance products and services according to the promise made to clients.
- Flexibility describes the operation's capability to change, vary or adapt operations activities to meet unexpected circumstances or individual customer preferences.

Operations performance can lead the business either to success or failure because it is the operations that give the organisation the capability to respond to customer needs and the ability to keep the organisation ahead of its competitors (Slack, Brandon-Jones, Johnston, Singh, & Phihlela, 2017).

2.5 Analytical Framework

2.5.1 *Resource-Based View Theoretical Framework*

The research uses the resource-based view (Barney, 1991). The theory is based on the premise that an organisation can achieve a sustained competitive advantage if it acquires and control resources and capabilities specific to the firm that are valuable, rare, inimitable, and non-substitutable (VRIN), plus the organisation (O) must be able to absorb and apply them (Barney, 2002).

Valuable resources can be utilised by the organisation to gain advantage on opportunities and neutralise competitors. Rare resources are not accessible to

most organisations and are not equally distributed across competitors. Inimitable resources are difficult to copy due to factors such as social complexity, casual ambiguity, and special historical circumstances. Non-substitutable resources cannot be easily replaced by other resources. The VRIO framework replaces non-substitutable with organisation-wide support. AI implementation must be supported and complemented by the organisation culture, structure, and processes.

These resources can either be tangible or intangible assets and can enable the organisation to create a competitive position and advantage, that drives high performance if they are safeguarded from being copied and substituted (Peterafa & Barney, 2003). Such resources can lead to superior quality, cost-competitive, fast delivery, high flexibility, and high dependability performance (Vilkas, Duobiene, & Rauleckas, 2020).

Information technology is considered a valuable resource that an organisation can use to improve product quality, reduce product development cycle time, and lower product development costs. AI is also viewed as rare and not easily copied or transferable that can enhance life insurance organisation capabilities and eventually lead to a higher performance.

2.52.6 Conceptual Framework

The conceptual framework aims to show the perceived impact of AI to operations performance where performance can be measured through cost, quality, speed, flexibility, and dependability as presented in Figure 2 below.

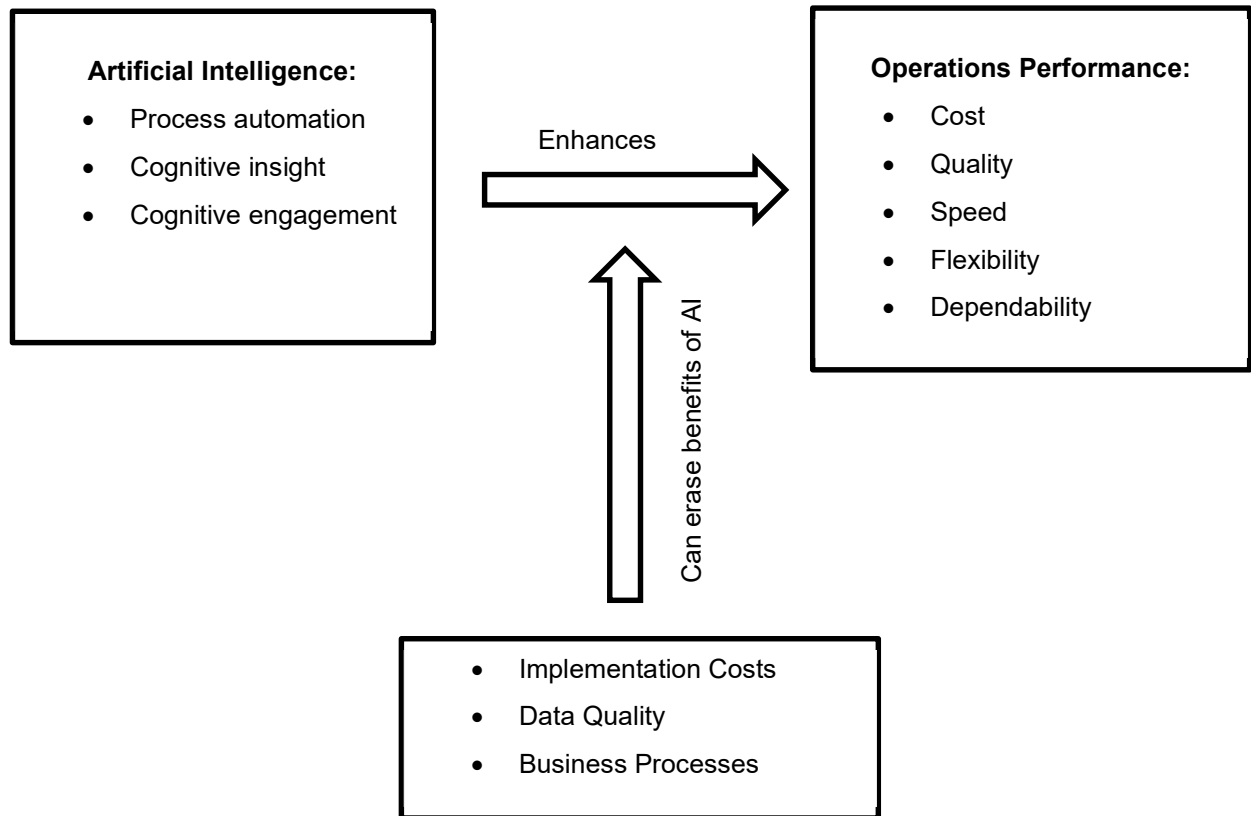


Figure 2: Conceptual Framework

2.62.7 Summary

The chapter began with the definitions of AI and operations performance. Then it looked at the history of AI including the AI summers and winters. Then the types of AI were discussed with narrow and general AI being the general classification of AI types. Another of discussing AI was discussed. Then the business needs that can be supported by AI such as process automation, cognitive insights and cognitive engagement were discussed. Then the literature looked at the AI applications used in insurance such as language or text conversion, trends or

patterns recognition, data-driven decision making. The impact of AI applications to operations performance of selected insurance organisations was also examined. AI was seen to have impacted how insurance companies interact with customers, automated processes and invented new markets and risks.

The literature then looked operations performance with cost, quality, speed, flexibility, and dependability being chosen as measures for operations performance.

Further the chapter looked at the theoretical framework guiding the study as being the resource-based view due to AI being viewed as a valuable, rare, not easily imitated or copied and organisation wide. Lastly, the chapter closes with a conceptual framework that shows AI having an impact on operations performance of the organisation.

The next chapter focusses on the research methodology of the study.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Research Approach

The research study used a qualitative approach to gather and understand the perceptions of managers and employees that have implemented and/or used AI technologies in life insurance organisations operations on how AI technologies have impacted operations performance of the organisations after the AI implementation. A qualitative approach is defined as a study of the nature of a phenomenon (Busetto, Wick, & Gumbinger, 2020). The phenomenon is how managers and employees (that have implemented and/or used AI) perceive AI has impacted their organisation's operations performance.

A qualitative methodology was the right approach as it aims to produce detailed participants' opinions and experiences regarding the studies phenomenon (Rahman, 2016). The use of semi-structured and questions that were open-ended enabled participants to share elaborate information on their experiences of how the implemented AI applications have enhanced operations performance. This methodology allowed for detailed data to be gathered to prove the research proposition.

This study followed a deductive approach and responses from the interviews were used to test the proposition that states that AI enhances the operations performance of an organisation as perceived by managers and employees that have implemented and/or used AI applications.

Assumptions for this approach were that:

- Operations managers and/or employees were forthcoming with information
- Supporting documentation were to be not requested due to sensitivity of certain information should they be seen by competitors
- Collected data from participants were to corroborate the research proposal that AI improved operations performance.

3.2 Research Design

The case study approach was used in this research as it enabled in-depth investigation of the phenomenon. The case study approach has shown great value in other fields such as business, law, and policy (Crowe, et al., 2011). Data was collected from various sources using one-on-one interviews and insights was drawn from the data.

The case study approach was appropriate because the research study aimed to explore and understand how AI can enhance operations performance in the life insurance industry in South Africa.

3.3 Data Collection Methods

The research data collection method was primarily one-on-one interviews conducted via an online medium such as Microsoft Teams and emails with managers and employees in systems, products, and operations departments. Interviews were made up of semi-structured questions that were open ended to allow the exploration, and probing areas of interest with participants. Interview responses were electronically recorded for later reference and analysis.

3.4 Population and Sample

The sections below focus on the population and sample selected for the research study.

3.4.1 *Population*

The target population was managers and employees that have implemented and/or used AI technologies in their functional areas. The reason for selecting managers and employees was because they have knowledge on how operations performed before and after the AI implementation.

3.4.2 Sample and Sampling Method

A purposive sampling method was applied. Purposive sampling is also known as judgement sampling due to favouring the deliberate selection of participants with certain qualities. Based on the phenomenon being studied, the researcher must decide what information is needed and must find the people that have the needed information. Participants must be willing and able to clearly articulate their experiences in both expressive and reflective manner (Etikan, Musa, & Alkassim, 2016).

The researcher defined the criteria and characteristics of people to be included in the research study. This was to ensure relevancy based on industry exposure and experiences, and therefore can give better insights into the research questions.

The selection criteria were, therefore, managers and employees with a reasonable amount of experience on using AI technologies in the organisation's operations. The selected people had the ability to discuss the performance of the work function/activity before and after the AI implementation. The Managers and employees were selected from different functional areas and different life insurance organisations. The research report summarises how the selected people perceive AI to have impacted operations performance of the life insurance organisations.

Table 3: Profile of Respondents

Population	Description of Respondent	Sampled Number
Managers and Employees that have implemented and/or used AI technologies within the life insurance industry	Chief Information Officers	1
	Enterprise Architect	1
	Business Architect	1
	Business Analyst	1
	Actuary (Data Science Lab)	1
	Head of Digital	1
	Digital Product Owner (Virtual Agents)	1
	Underwriting Manager	1
	Finance Operations Consultant	1
Total Number of Respondents		9

3.5 The research Instrument

The interview guide was made up of research questions around the understanding of AI by the managers and employees, the state of AI implementations and the impact of AI technologies in operations performance of life insurance organisations within the industry. All interviews were conducted online due to the COVID-9 restrictions. Please refer to appendix A for the research instrument.

3.6 Procedure for Data Collection

Data was collected from participants using an online platform and employing one-on-one approach for interviews that were made up of semi-structured questions that were open-ended.

Heads of department were requested to nominate participants that were able to contribute on the research topic from the functional areas that implemented AI. The reason for approaching heads of department was to get buy-in and to create awareness that participants may need some time out their calendar to do the interview.

Before the interview began, it was explained to the participants that data collected from the interview session was not going to be used for anything else besides the academic purpose of the research project. Permission to record the interview for later referral and data analysis was asked from participants. Recording of the interview session only happened with the participant's consent.

The participants were taken through the interview questions and their answers were recorded. Follow-up questions were posed to participants where necessary to get clarity or more facts around the areas of interest. All interview responses were stored electronically through a password protected device for later reference and analysis. Participant names were not used or revealed outside of the data collection process.

3.7 Data Analysis and Interpretation

Thematic analysis was broadly used because of its flexibility and easiness to learn (Clarke & Braun, 2013). This type of analysis allowed for the discovery of patterns and trends across data sets (Braun, 2019). Since this was a qualitative approach, the data on the perceptions AI impact to operations performance was collected and analysed to determine if it corroborated with the research proposition. The data was analysed according to the five operations performance objectives.

Data analysis on quality focused on products' overall quality and conformance to specification. High products quality and conformance to specification corroborated the proposition that AI implementation enhanced operations performance.

Cost analysis focused on the cost of operations. Lower operations costs corroborated the proposition that AI implementation enhanced operations performance.

Analysis on speed focused on how quickly the requested products and services got delivered to clients. Quick delivery of products and services to clients corroborated the proposition that AI enhanced operations performance.

Dependability analysis focused on the timeliness of products and services to clients (i.e., on-time delivery). On-time delivery of products and services corroborated the proposition that AI enhances operations performance

Flexibility analysis focused on the ability to change production volume, product mix, production time and product innovation. High flexibility of operations corroborated the proposition that AI enhances operations.

3.8 Limitations of the Study

Due to the small sample size of participants, the study may not be the ideal for generalisation to other contexts.

3.9 Transferability and Dependability

3.9.1 *Transferability*

Transferability describes the degree to which the research outcomes can be used in other research settings or context with other participants. Transferability can be facilitated using descriptions (Korstjens & Moser, 2017). The data that was provided for transferability purposes included the area of research in AI and operations improvement, the description of the managers and employees sample, the sample size, and the interview questions.

3.9.2 *Credibility*

Credibility describes the confidence one has that the research results represent the truth of the participants' original data and interpretations (Korstjens & Moser, 2017). Credibility was achieved by selecting the appropriate participants with the relevant knowledge and exposure to AI and operations management in the life insurance industry.

The appropriate sample size for the study was a minimum of one manager or employee per functional area that has implemented an AI application. No documentation on AI impact to operations performance was collected as evidence to support the research findings. As in Creswell (2013), feedback was obtained from the participants on their views of the credibility of the findings and interpretations. The feedback process involved playing back the data, analysis, interpretations, and conclusions to the participants so that they can give their own judgement on the accuracy and credibility of the information. Participants were also be given access to research questions and research summary upfront to familiarise themselves with the content.

3.9.3 *Dependability*

Dependability refers to documentation of the research steps from the initiation to the end of the research project (i.e., report findings) (Korstjens & Moser, 2017). The audit trail was used to ensure that data is dependable and consistent.

A complete set of notes was kept on decisions made during the research study, such as meeting minutes, recordings, interview findings data analysis, and reporting.

3.10 Ethical Considerations

To ensure the research is ethical, permission to conduct interviews with participants was obtained from the Wits Business School Ethics Committee. Also, permission to interview participants was obtained from the organisations of interest.

Once permission was obtained, participants were identified, and the initial contact was made to describe the purpose and goals of the study. The participants were asked if they were interested in participating in the study. It was made clear that participating in the research study was purely voluntary and that participants would not be exposed to any form of risk. Consent forms were provided to the participants that agreed to participate in the study, and participants were not forced to sign them.

The research interviews were conducted electronically (i.e., via Microsoft Teams and emails), therefore there were no requests for on-site visits. A meeting invite was sent to participant's availability. Interviews were undertaken during working hours and were kept to a maximum of one hour. Follow-up questions were done over emails where it was necessary.

Interview questions were not designed such that responses were biased to the proposition claimed by the study. All interview response (i.e., both positive and negative) were captured for analysis. Interview responses and were played back to the participants.

The study did not falsify any evidence, findings, data, or conclusions. The study did not disclose any information that was harmful to the participants. The study ensured that communication was clear and appropriate.

Table 4: Consistency Table: Research Questions, Propositions, Data Collection and Data Analysis

RQ #	State Research Question or Objective	Proposition#	State Proposition	Data collection detail	Data analysis method
1	Does AI improve the operations performance of life insurance organisations within the South African life insurance industry?	1	AI can enhance operations performance of life insurance organisations within the South African industry by maximising the five operations performance objectives.	Interview guide in Appendix A	Thematic analysis

3.11 Summary

The focus of the chapter was on the research methodology selected for this study. The qualitative approach was discussed together with data collection methods and population sample. Further the chapter, discussed the research instrument, data collection procedures, data analysis and interpretation. Limitations of the study were also highlighted. The transferability and dependability were discussed followed by ethical considerations and the consistency table.

The next chapter focuses on the presentation of the findings

CHAPTER 4. PRESENTATION OF FINDINGS

4.1. Introduction

AI technologies are increasingly getting implemented in many industries including life insurance. AI can be viewed as a valuable technology resource used by organisations to improve performance and stay competitive. But do managers and employees see the impact of AI in the organisations' performance? The purpose of the study is to understand how managers and employees perceive AI to impact the organisation's operations performance in the life insurance industry.

The research objectives include:

1. Investigating the understanding of AI in the life insurance industry
2. Investigating the state of AI implementations and AI applications that have been implemented
3. Understanding the reasons behind implementing AI technologies
4. Understanding how AI is perceived to have impacted operations performance using the five operations objectives

The study uses a case study approach to do in-depth one-on-one interviews with participants that were chosen based on their role and experience in life insurance and AI technology. People without any experience in life insurance and AI technology were not selected to ensure high quality of the study.

4.2. Purpose of the Chapter

The purpose of this chapter is to present the research results based the objectives of the research discussed above. The study starts by discussing the background information of the participants, followed by the findings and the conclusion

4.3. Background Information on Participants

The section describes the roles of the participants that were interviewed for this study.

Purposive sampling was applied in selecting participants via LinkedIn and through referrals. Twenty participants were identified based on role, experience, and industry. Nine participants agreed to partake in the study and the eleven did not respond to the request to participate. Of the nine participants, two were executives (i.e., a CIO and a head of digital), one was an enterprise architect, a business architect, a business analyst, an actuary, a digital product owner, an underwriting manager, and a finance administrator. All participants have sufficient experience in life insurance and have implemented or used AI technologies to perform work activities. The participants come from different life insurance organisations.

The data that was collected was analysed using thematic content analysis using the Atlas.ti 22 software and Microsoft Excel. Presentation of results was made using quotes, tables, graphs and pie-charts.

The major study themes/codes arising from the data, includes the understanding of AI, the state of AI implementation within the life insurance companies, and the impact of AI implementation to operations performance of the organisation.

The next sections discuss findings based on research objectives

4.4. Understanding of AI in the Life Insurance Industry

As a building block to the discussion on implications of AI within the life insurance industry, participants were asked to indicate their understanding of the term 'AI'. Virtually all participants were able to demonstrate a good understanding of AI, its applications, and general implications for their respective organisations. Key words used to describe AI by participants include intelligent agents, mimicking human intelligence, automation of repetitive tasks, use of data to improve &

predict, and others. Participant 3 defined AI as *a software that can emulate many aspects of human cognition and behaviour, for instance speech or image recognition, complex decision-making, prediction, among others*. Participant 1 defined AI as *the ability of machines or computer systems to mimic the human mind. In other words, the ability to either automate repeatable tasks or to find predefined patterns in large volumes of data*.

Figure 3 summarises some of the key quotations made by participants on their understanding of AI.

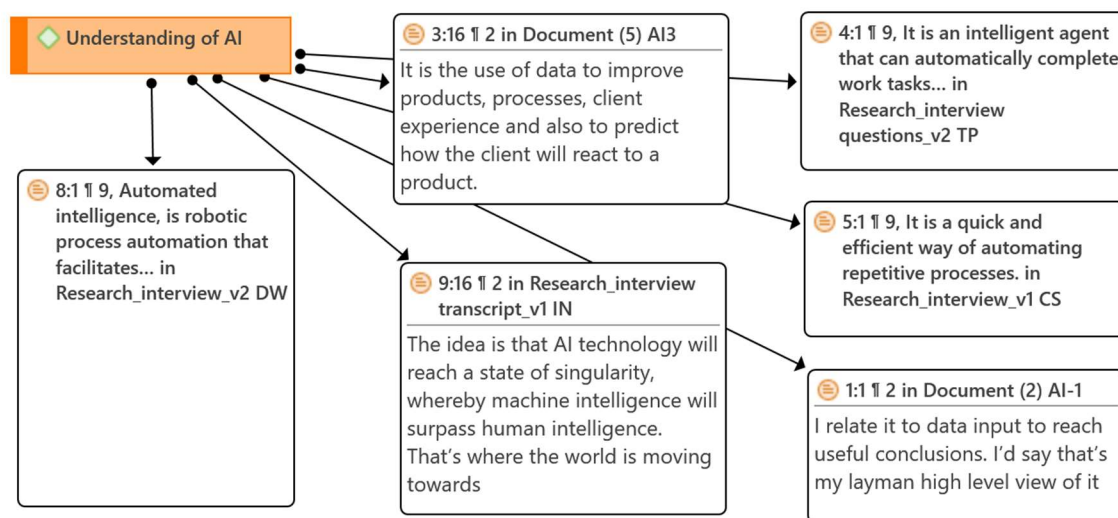


Figure 3: Participants understanding of AI

4.5. State of AI Implementation Within Life Insurance Organisations in SA

The study also sought to establish the state of AI implementation within life insurance companies in South Africa. The first question was to understand the participants view of the AI implementation state in their respective company and when was the first implementation made.

From the data collected, it was found that most AI implementations were still in the early stages. The participants answered as follows: participants 4, 5, 6, 7,8 & 9 described the state of AI implementations to be in the *early stages*. These AI

implementations are between one and three years old. Participant 1 described the AI implementation state as *growing*. When asked when the first implement was, his view was that there was no exact start date he sees AI as *an evolution with no starting space*. Participant 2 chose to use the words, *great state* as the company started the AI implementation journey 5 years back in 2017 and *they were among the first to implement AI in the world*. Participant 3 described the state as *medium in South Africa, low/medium when compared to digital start-ups and low when compared to the US, China, etc.*

The below table shows the participants responses in terms of the state and year of implementation.

Table 5: AI Implementation State and Year of Implementation

Participant	AI Implementation State	Year of implementation
Participant 1	Growing	No defined start date as AI implementation is seen as an evolution
Participant 2	Great state	2017
Participant 3	Medium in SA Medium/low compared to native digital start-ups Low compared to US, China, etc.	2018
Participant 4	Early stages	2020
Participant 5	Early stages	2021
Participant 6	Early stages	2019
Participant 7	Early stages	2020
Participant 8	Early stages	2020
Participant 9	Early stages	2018

The second question was to understand the AI application that was implemented by the participant's company. The below table presents the participants' responses:

Table 6: AI Applications Implemented in the Different Life Insurance Companies

Participants	Implemented AI Application
Participant 1	Robotics process automation Cognitive insights Cognitive engagement
Participant 2	Robotics process automation
Participant 3	Cognitive insights Cognitive engagement
Participant 4	Robotics process automation
Participant 5	Robotics process automation
Participant 6	Robotics process automation Cognitive insights
Participant 7	Robotics process automation
Participant 8	Robotics process automation
Participant 9	Robotics process automation Cognitive insights Cognitive engagement

Participants were also asked to indicate departments/areas where AI technologies were implemented in their respective organisations. The departments mentioned by participants include new business, underwriting, servicing, claims, finance, claims, data science, and marketing. Table 7 below shows the departments, as well as how AI has been applied in those areas.

Table 7: Departments that Implemented AI Technologies

Department/ area impacted	How AI has been applied in the area
New Business	Applications processing
Underwriting	Underwriting processing
Servicing	Automated emails routing
Claims	Straight-through claims processing
Finance	Processing and disbursement of customer claims
Marketing operations	Google return on ad spend bidding Market segmentation

Department/ area impacted	How AI has been applied in the area
	Data mining & targeted marketing
Data Science	Readmission models Disease risk prediction

4.6. Reasons for Implementing AI Technologies in the Selected Life Insurance Organisations in SA

Participants were asked to indicate the reasons behind their AI implementations in their respective organisations. From the results collected, the reasons for implementing AI were summarised and categorised into the below push & pull factors.

Push factors include too many mundane administrative tasks, too many manual processes, using multiple systems to complete a process and elimination of human errors.

Pull factors include reasons such as alignment to organisational strategy and objectives, better client experience, services that are always available to customers 24/7, driving down costs, ability to service members on a large scale, building an organisation for the future and the accumulation of fantastic data. Table 8 below shows reasons as given by participants.

Table 8: Reasons for Implementing AI

Participants	Reasons for Implementing AI
Participant 1	Alignment to organisation values & objectives
Participant 2	Machines don't have headaches It works 24/7 Better client experience Consistent client experience
Participant 3	Accumulation of fantastic data made the development of AI tools feasible

	Conceptualisation of value-add use cases for customers, and the business Seeing AI investments within life insurance overseas
Participant 4	There were too many small administrative tasks that were time consuming within the finance payment process
Participant 5	Reduce lots of manual business processes that were time consuming
Participant 6	Users were using multiple systems to execute one process Users had to copy information from third party to company systems
Participant 7	Elimination of human errors such as paying wrong claims Reduce costs Innovation in ways of working
Participant 8	Client frustrations Being behind other organisations & wanting to build an organisation for the future
Participant 9	Need to service members on a large scale Need to offer better client service Drive down costs

4.7. The Perceived Impact of AI to Operations Performance

In this study, a question was posed to participants on how the implementation of AI has impacted operations in their respective organisations. In answering this question, several participants associated AI implementation with specific operational improvements in cost saving, service quality, processing speed, flexibility, and dependability of services, which will be discussed in the coming subsections. Other participants identified improvements from AI implementation such as increasing direct sales using recommender systems, improving the finance function through the automation of repetitive processes, as well as freeing up staff in operations to pursue more complex tasks.

Figure 4 below shows some of the selected quotations from participants on operational impacts of AI.

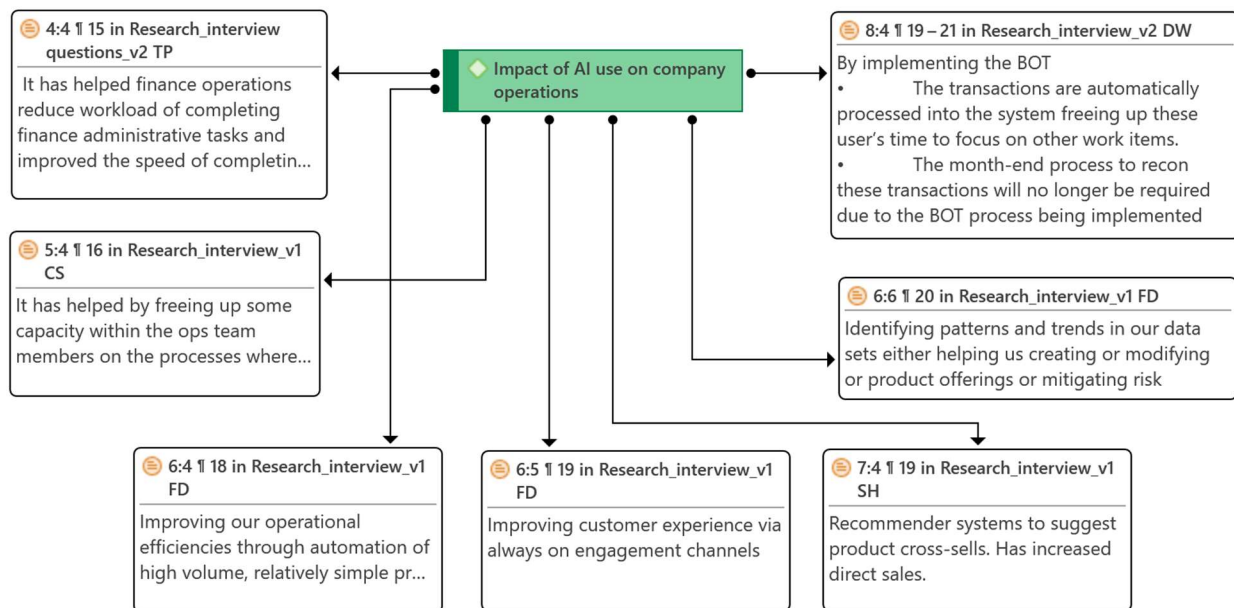


Figure 4: Impact of AI implementation on operations performance

However, it was also indicated by participant 9 that operations performance improvements cannot be solely attributed to an AI application as in some instances people may be needed in the process for empathy, discretion and understanding. Human ability to collaborate with the machines was viewed as a key ingredient in the improvement of operations performance.

The below sections look at data collected on how AI implementation has impacted operations performance of the selected life insurance organisations based on cost, quality, speed, flexibility, and dependability.

4.7.1. Impact of AI Implementation on Cost

Participants were asked how the AI technology that was implemented by the organisation impacted operations cost. Of the 9 participants, 4 participants (44%) indicated that operations costs were reduced due to removing a person from the process, quicker turnaround times in paying a claim meant that taking out accumulated interest on claims waiting payment. Another 4 participants stated that costs increased due to acquisition of software, hardware, license fees, training costs and hiring of new skills. 1 participant did not see any impact on

operations costs since AI implementation does equate to retrenchment, but employees get to focus on other tasks, and some are moved to other areas.

Figure 5 summarises selected quotes from participants around impact to operations costs.

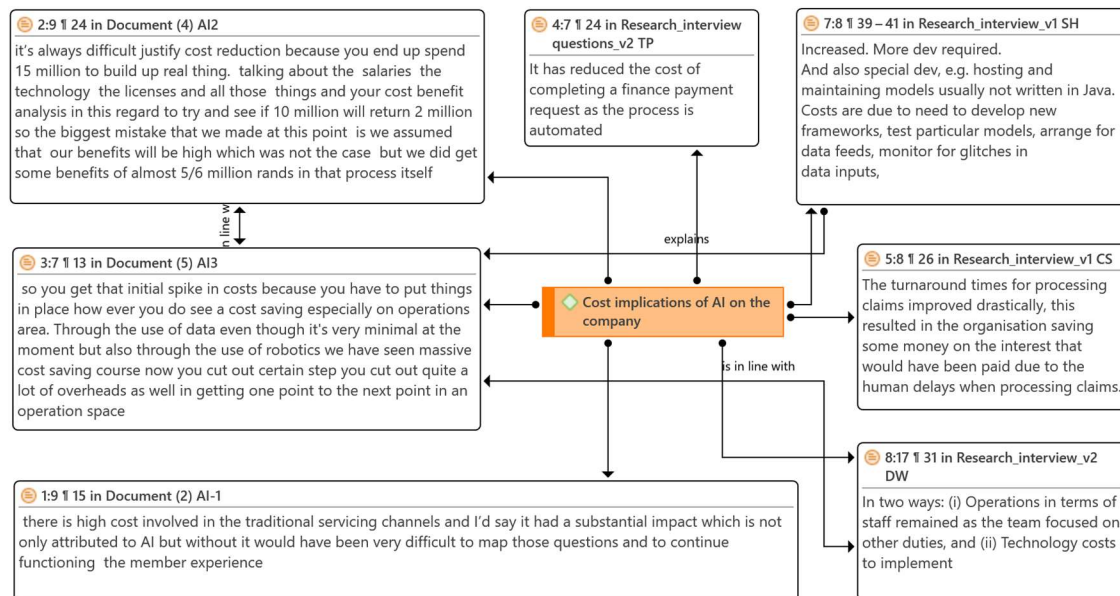


Figure 5: Impact of AI to Operations Cost

It is important to note that participants 8 & 9 noted that the spike in operations cost eventually came down after some time following the implementation of the AI technology.

Participants were further asked to indicate which specific costs were impacted by AI within their organisation, and in what ways. Table 9 below summarises results on the type of costs that have been impacted by AI implementation.

Table 9: Costs impacted by the adoption of AI within life insurance companies

Cost Types	How AI has Impacted these Costs
Human costs	- Cost reduction due to some staff members being replaced by AI - Less new hires due to automated processes - Costs to train staff on new systems

	- Costs to train staff that moved to other areas - Costs of hiring data scientists
Technology costs	- Acquisition costs for new AI system - Development costs - Hardware costs - License fees
Transaction costs	- Lower transaction costs - Lower floor space costs
Compliance costs	- Compliance on data usage

As shown on Table 9 above, AI implementation within life insurance companies has resulted in both increase in costs at the inception of the AI implementation and eventually the realisation some cost savings after the implementation. Overall, participants indicated a positive outlook of AI adoption that promises long-term cost savings, despite the initial spike in operational overheads.

4.7.2. Impact of AI Implementation on Quality

Participants were asked first to indicate whether they believed AI implementation in their respective companies has improved quality, then asked to indicate reasons why they thought AI adoption has improved quality. From the study findings, all nine study participants indicated that they thought AI adoption in their respective organisations has improved quality. When asked to elaborate, participants indicated the following ways in which quality was improved by AI implementation:

- The reduction/ elimination of human errors in data capturing, customer query handling, risk profiling, and claims processing
- Improved turnaround times
- Ability of AI to tailor services and responses to specific customer needs
- AI systems are more consistent/ uniform in their work
- Automated monthly reconciliation activities
- Interfacing with customers 24/7

- Targeted marketing activities
- Better client experience
- Better customer insights

However, it was also noted from some responses that quality improvements have to be attached to a set of conditions that should work together with AI technology to enhance quality. Specifically, there is a need for good quality raw data to be fed into the AI systems so that accurate decisions can be made. Poor quality data can lead to trust issues with the AI system. Moreover, AI technology requires efficient business processes to ensure automation works to enhance the processes, and not try to rescue the processes from inefficiencies. The following quote from Participant 9 attests:

“If we are purely talking about process automation, then it is critical to understand that AI driven process automation is heavily dependent on the quality of the data and the process itself. Automating inefficient processes leads to the same challenges that a process had previously, only it happens faster.”

4.7.3. Impact of AI Implementation on Speed

Of the nine study participants who answered the question on the impact on speed, eight indicated right away that they thought AI applications had improved processing speed, while participant 3 indicated that speed had improved but to some extent. The reasons given by participant 3 were complex set up, building models and data pipelines.

Participants that indicated that AI enhanced speed were asked to indicate the specifics of speed improvements. Participants indicated that improvements were seen in speedy client responses, client enquiry handling, claim straight-through processing, claim payment requests and shortened time in product development. Figure 6 below shows some selected quotations of AI impact to speed in operations performance.

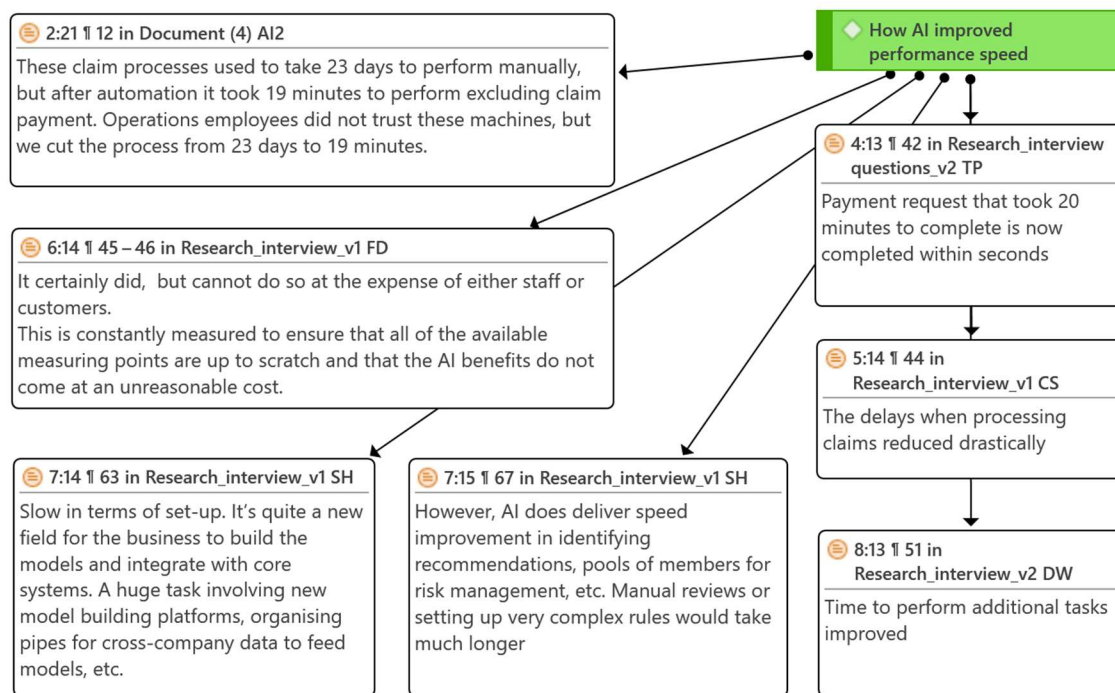


Figure 6: How AI adoption improved performance speeds within life insurance companies

It can be seen from the selected quotes in Figure 8 above that there was big speed improvement after the automation of some processes such as claims, where processing time was reduced from 23 days to 19 minutes as stated by participant 7. Also, payment requests processing time was reduced from 20 minutes to within seconds as stated by participant 4. The time reduction led to consultants having more time to perform other tasks.

In addition, while participant 3 noted that the process of AI setup was slow and complex, processing speed had improved on average since implementation.

It is worth mentioning that while AI improved speed in operations, missing information or documents can slow down the processing speed as noted by participant 8. Also, complex tasks will always require human intervention such as empathy, discretion or understanding which can slow down the speed of the process as noted by participant 1

4.7.4. Impact of AI Implementation on Flexibility

Of the six participants who answered the question on flexibility of services, four (66%) indicated that they have seen flexibility improvements after the AI implementation, while two (34%) said they have not seen any flexibility improvements. Participant 3 stated that AI has given them more information on what to change, e.g., the sales recommendation mix or amounts to bid for digital advertising. Also, participant 3 mentioned that AI technology has made the organisation to become more flexible in accommodating new kinds of opportunities brought by AI.

The below table shows the participants that viewed AI technology to have improved flexibility:

Table 10: Flexibility Improvement

Flexibility Improvement	Participants
Change in production volume	Participant 6
	Participant 7
	Participant 8
Change in product mix	Participant 3
	Participant 6
Cater for customised customer requests	Participant 1
	Participant 2
	Participant 5
	Participant 6
Innovate or introduce new products	Participant 1
	Participant 3
	Participant 5
	Participant 6
	Participant 9

For those that admitted to seeing flexibility improvements, it was reasoned that AI implementation has improved flexibility of developing new products, customisation of products/services to unique client needs, and changes in the product mix.

Figure 7 below shows some of the quotes from participants relating to flexibility improvement.

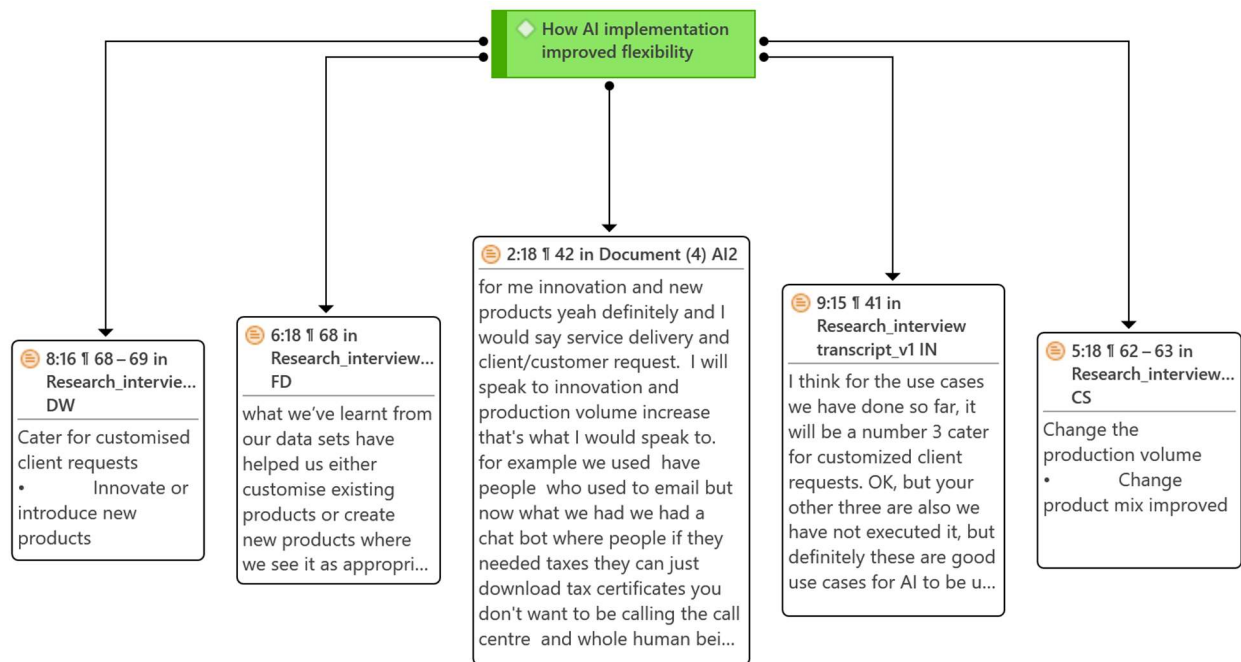


Figure 7: How AI adoption improved flexibility within life insurance companies

On the other hand, the participants who indicated to not have seen improvements in flexibility stated that the major reason was that processes within their organisations still rely largely on human input, hence AI has not necessarily improved flexibility. This is attested by the following quote from Participant 8:

“I think in terms of those elements we are still dependent pretty much on a human being, but also because there are certain skills that we require within our field such as actuaries and underwriters, it’s a specific skillset that is required to do certain functions.”

4.7.5. Impact of AI Implementation on Dependability

In Of the nine participants that answered this question, seven (78%) indicated that they have seen improvements in dependability, while two (22%) said they have not seen any dependability improvements. Dependability improvements were supported by observations of improvements in processing speeds, 24/7 systems availability that ensured customers always get assistance when needed, and keeping promises made to customers. Below are selected quotes from participants on dependability.

Participant 7 detailed how the use of an *always-on* system has improved operations:

“Our clients when they interact with us on emails, SMS or WhatsApp, there’s no human being who manages those inboxes. It’s the machine that reads the email, documents, makes sense of what the client is trying to achieve from the request. It then executes the request where possible and responds back to the client in terms of whatever is needed by the client.”

Other participants were quoted as follows: Participant 1 mentioned that *AI system is available 24/7 to clients*. Participant 4 stated that, *the speed of completing payment requests has improved our SLAs*. Participant 8 noted that, *AI has improved client experience and dependability of our services*. Lastly, participant 9 mentioned that *AI has helped the organisation with timely responses to clients*.

4.8. Summary

The study sought to explore and understand how managers that have implemented AI perceive AI applications to have enhanced operations performance within their respective organisations in the life insurance industry. This chapter focused on the presentation of findings of data arising from in-depth interviews conducted with nine participants. Findings of the study showed that

participants were generally conversant in their understanding of AI and were able to explain the extent of AI use within their respective organisations. A review of the motivations for AI adoption in the industry found that companies were influenced by the need for faster processing, less human errors, and uninterrupted operations in their adoption of AI. Meanwhile, AI implementation was found to have positively impacted operations performance through quality services, speedy processing, flexibility, and dependability of services. Cost reduction was difficult to justify due to high implementation costs. From several contributions, however, it was also noted that the use of AI has not led to complete replacement of manual processes which are still necessary in areas such as actuarial. As a result, marked improvements in key areas are also attributable to human interventions, not just AI use.

CHAPTER 5. DISCUSSION OF FINDINGS

5.1 Introduction

The life insurance industry is a very competitive industry. Companies are forced to continuously innovate to remain competitive. The study uses the resource-based view and classifies AI technology and the skills to develop, maintain and use the technology as resources and capabilities that are valuable, rare, hard to copy, and difficult to substitute.

Organisations, including life insurance companies are increasingly implementing AI technologies to achieve a competitive edge. The covid-19 pandemic has fast tracked AI implementations through lockdowns and work from home. However, does AI improve the operations performance of the organisation from the point of view of managers and employees?

The study's objective was to investigate the perceptions of managers and/or employees on how AI applications that have been implemented by life insurance organisations have impacted their organisation's operations performance. The study used a qualitative approach whereby nine participants were interviewed using open ended questions. The interviews were conducted in the period between December 2021 and February 2022. Participants included a mix of executive managers to administration consultants in both operations and technology departments of different organisations.

This chapter interprets the main findings of the research study in accordance with the research objectives. The research objectives are as follows:

1. To investigate the understanding of AI within life insurance in S.A.
2. To investigate the state of AI technologies within life insurance organisations
3. To identify AI applications in selected life insurance organisations.

4. To understand how AI is perceived to have improved operations performance of selected life insurance organisations using the five operations objectives

5.2 Summary of Findings

5.2.1 *The understanding of AI within the life insurance industry in South Africa*

The first research objective was to investigate the understanding of AI within the South African life insurance industry.

Participants demonstrated a good understanding of AI when asked to define AI in their own words. Keywords that participants used in their definitions include intelligent agents, mimicking of human intelligence, automation of repetitive tasks and the use of data to predict and improve processes and products.

All these keywords used by the participants are synonymous with artificial intelligence. Intelligent agents are known for their ability to interact with users using natural language (Feine, Gnewuch, Morana, & Maedche, 2019). Earlier forms of intelligent agents were limited to responding to simple customer enquiries by matching a user input against stored values (McTear, Callejas, & Griol, 2016). However, intelligent agents of today are more advanced as they use natural language to respond to more complicated customer requests (Knote, Janson, Eigenbrod, & Söllner, 2018).

Automation of repetitive tasks involves the use of software robots that can perform repetitive tasks accurately. Robotic process automation mimics how a human would interact with a system user interface to perform a series of tasks (Aalst, Bichler, & Heinzl, 2018).

Keywords used by participants are in alignment with the definition of AI by Lee & Yoon (2021) that defines AI as the imitation of human intelligence in machines like robots or computers that are automated to simulate cognitive functions that reflect problem solving abilities of humans

An interesting point, however, is that none of the participants mentioned learning, which is also a key aspect of AI. Also, one participant mentioned AI aiming to reach a state of singularity but also noted that AI was currently very far from that state.

5.2.2 *The State of AI within the selected life insurance organisations*

The second research objective was to investigate the state of AI within the selected life insurance organisations in SA.

The results show that most participants were of the same view that AI was still in its infant stages in their respective companies. The oldest AI implementation dates to five years ago in 2017 (see Figure 7 below). The year 2020 saw the most implementations of AI technologies in the companies in this study. This spike in AI implementations coincides with the beginning of Covid-19 pandemic whereby lockdowns and work from home was seen to have accelerated digitalisation to be a norm (McKinsey & Company, 2020).

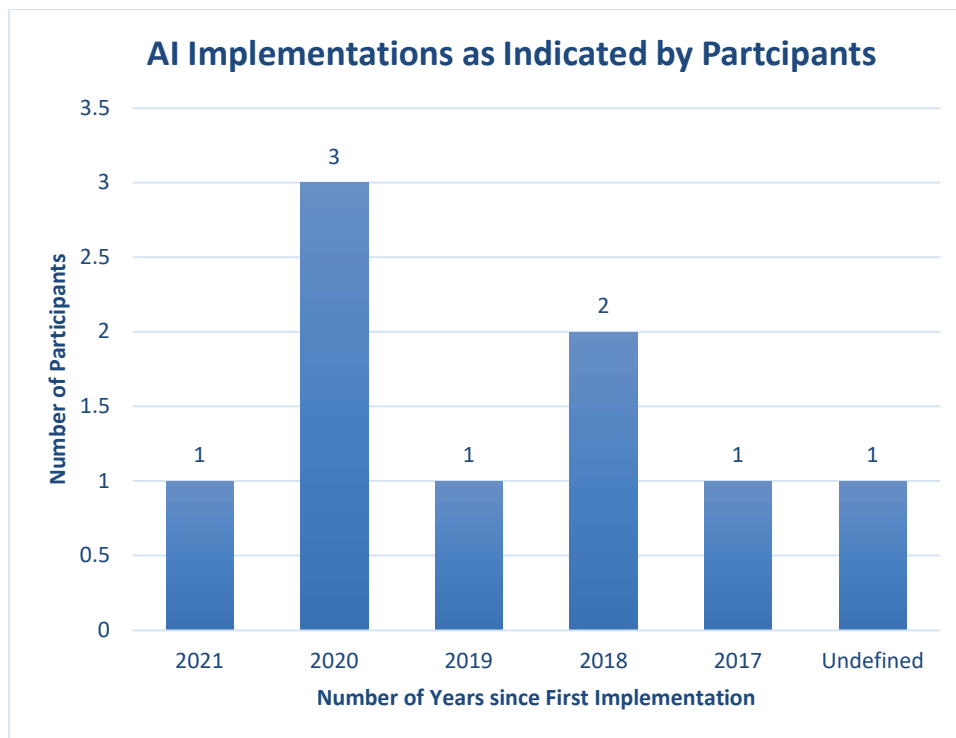


Figure 8: AI Implementation duration in years across different life insurance companies in SA

It must be noted that one participant described the implementation of AI as evolutionary without a specific start date.

5.2.3 AI Applications implemented within the selected life insurance organisations

The third research objective was to find out the AI technologies that have been implemented in the selected life insurance organisations.

The three applications of AI, i.e., process automation, cognitive insights and cognitive engagement stated by Davenport and Ronanki (2018) were prevalent in the life insurance organisations with process automation implemented the most, followed by cognitive insights and lastly cognitive engagement being the least implemented (see Figure 9 below).

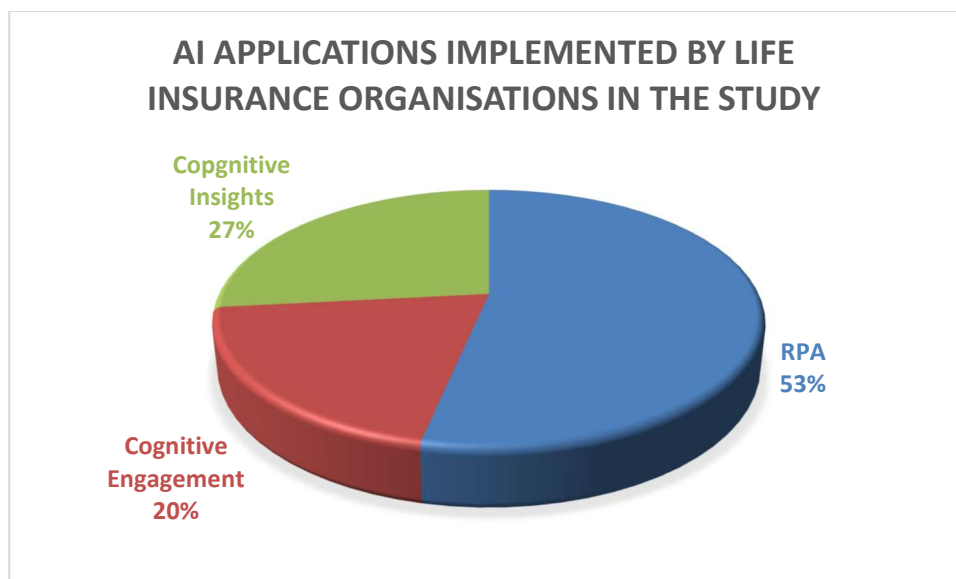


Figure 9: AI applications implemented by life insurance organisations in study

With reference to Figure 9 above, process automation was the most applied AI with eight (53%) participant mentioning RPA as the AI technology implemented, followed by cognitive insights through recommendation systems, re-admission models and disease risk predictions with four (27%) participants and lastly, cognitive engagement (i.e., chatbots) with three (20%) participants.

5.2.4 Reasons for Implementing AI Technologies in the Selected Life Insurance Organisations in SA

The third research objective was to understand the reasons that led companies to implement AI applications.

Various reasons for implementing AI were given by participants such as elimination of human errors, elimination of using multiple systems to complete work activities of a process, too many mundane administrative tasks and reduction of manual tasks. These reasons are in alignment with Fung's (2014) theory on processes that are suited to RPA. Fung lists characteristics such as low cognitive tasks, high volume tasks, tasks that are completed in multiple systems and tasks that are prone to human error.

Reasons of implementing AI from participants such services that are available to clients 24/7 and the desire to service clients on a larger scale are in alignment with theory on benefits of chatbots by Davenport (2018) which include 24/7 service to customers, lower error rates, ability to scale based on demand and freeing agents to work on complex tasks. It is worth mentioning that participants did indicate that because of AI implementation, agents had more time to complete other tasks.

Also, participants mentioned improved accuracy in predictions and recommendations to clients as benefits of AI implementation. These benefits are important to mention as they align with reasons for implementing AI by Davenport (2019) stating as one of the reasons for implementing cognitive insights is to predict or recommend what a customer might buy.

5.2.5 The perceived impact of AI to operations performance using cost, quality, speed, flexibility, and dependability as operations performance objectives

The fourth research objective was to understand the perceived impact of AI to operations performance using cost, quality, speed, flexibility, and dependability.

a. Cost

The study revealed two opposite views on the impact of AI on operations costs, with one half of the participants indicating cost reduction while the other half indicating a spike in operations costs.

Reduction in operation costs was due to the elimination of human interaction with the process therefore reducing transaction costs. Also, quicker turnaround times meant quick payment of claims, therefore reducing interest accumulation on loan insurance claims. These findings align with literature from Davenport (2018) that states that AI can help organisations cut costs and increase the quality of services, productivity, coordination, and efficiencies.

However, AI implementation comes with costs, like any information technology project. Costs, include acquisition of software, hardware, licence fees, training costs, new skills acquisition, and development costs. Organisations may undermine these costs when doing cost benefit analysis but may cause a big headache for management during after the implementation of the AI technology. Jafari (2014) concurs by stating that most organisations fail to fully consider all costs related to a particular technology implementation. Moreover, the identification and allocation of technology implementation costs is complex due to the types of costs within and outside of the technology function.

The huge implementation costs at the beginning of the AI project usually fall away with time but it may be risky to drive an AI implementation use case solely on cost reductions as cost benefits may not be immediately achieved.

It must be highlighted that AI implementations come with huge upfront costs that may undermine cost benefits that were planned to be achieved. Also, it may be risky for an organisation to use cost benefit as sole driver to implement AI technology.

b. *Quality*

The study found that the use of AI technology improved quality through better client experience, customer insights, less human errors, 24/7 availability of services. These findings align with literature by Ameen, et al (2021) that states that AI improves customer experience by increasing the knowledge the company has on its customer preferences and patterns of behaviour.

It is also important to highlight that quality and AI system trust can be negatively impacted by poor quality data used by the AI system. This is supported by theory from Redman (1998) that states that poor quality of data leads to trust issues with system, low employee morale and difficulties in putting the project in order. Poor data quality at an operational level can decrease customer experience, decrease employee satisfaction, and increase costs. Re-engineering may also be difficult.

c. *Speed*

The study found that AI implementation drastically improved the speed of operations performance as automated processes removed delays and human intervention from processes. This finding agrees with literature by Tariq, et al (2021) that states that AI allows for speedy analysis, processing and acting in accordance with the data. However, not all work activities can be automated, as human intervention will always be needed to deliver activities that need discretion, understanding and empathy. Srinivasan & González (2022) agree with this finding as they state that AI's limitation is empathy. Carpenter (2015) adds that AI does not create a world of man versus machine but rather a world of man and machines. Therefore, AI is there to augment employee capabilities in achieving their work objectives. Human intervention may lead to delays therefore reducing the operations speed.

d. *Flexibility*

The study found that AI implementations increased flexibility of operations through improved flexibility in customising customer requests, product innovation and product mix. These findings align to literature from Vilkas et al. (2020) that states that AI can lead to high flexibility in services provided. Fracapane et al. (2020) also concurs by stating that emerging technologies such as AI increase flexibility in systems.

The minority that didn't see any improvements in flexibility mentioned that the cause was due manual input that is still needed from actuarial and underwriting teams.

e. *Dependability*

The study found that AI applications has increased dependability in operations through services that were available to customers 24/7, provision of timely responses to clients as promised, improved SLAs internally which led to better

client experience. These findings are in alignment with literature from Vilkas et al. (2020) that states that AI as can lead to high dependability.

5.3 Summary

The study aimed to investigate how managers that have implemented AI perceive AI applications to have enhanced operations performance within their respective organisations in the life insurance industry. The study explored this investigation by using four research objectives. First, the study wanted to find out about the level of AI understanding within the life insurance industry. Participants displayed good level of understanding when describing AI in their own words. The key words they used were all in the AI definition used by this research study but a keyword that was missing was “learning”. The second objective was to investigate the state of AI within the life insurance industry. Participants indicated that AI was still in its infant stages with the oldest implementation being 5 years back and with a spike in implementations in 2020 which coincides with the Covid-19 pandemic period of lockdowns. The third research objective was to identify the AI implementations in the industry. All three AI applications are prevalent with process automations being the most implemented, followed by cognitive insights and lastly cognitive engagement. The fourth research objective was to understand how AI is perceived to have enhanced operations performance using cost, quality, speed, flexibility, and dependability. Participants indicated that AI did reduce operations costs over time, but they come with very high costs and cost benefit must not be the main driver of the AI use case. AI implementations enhance the quality-of-life insurance products and services, but data quality is key. The speed of services is enhanced by AI technologies, however not all work activities can be automated as some activities needed empathy and discretion. Flexibility in customisation, innovation and product mix was found to have been improved by AI technologies. Lastly, participants also agreed that AI implementation had improved dependability of services offered to clients.

These findings agree with the proposition of this study that AI can enhance operations performance by maximising the five operations performance objectives.

CHAPTER 6. CONCLUSION & RECOMMENDATIONS

6.1 Conclusion

The purpose of this study was to investigate how managers and employees perceive AI to have enhanced operations performance within their respective organisations in the life insurance industry in South Africa. The study's approach was to investigate the level of AI understanding within the life insurance industry, the state of AI implementations and AI applications that have been implemented, the reasons behind AI implementations and lastly, the perceptions managers and employees that have on how AI has improved the operations performance of life insurance organisations.

The study found that there was a good level of AI understanding within the South African life insurance industry. This was evident in the keywords used to define AI.

The state of AI implementations is viewed to be still in the early stages due to most of the AI technologies being implemented within the last five years. Process automation was the most implemented AI technology, followed by cognitive insights and cognitive engagement with least implementations.

The reasons found to be the driving force for AI implementations are the eliminations of human errors, mundane administrative tasks, and use of multiple systems to complete a work task. Also, the need to provide client services that are accessible 24/7 and service clients on a larger scale.

AI was perceived to have generally enhanced operations performance of the studied life insurance organisations. AI technologies were viewed to have reduced transactions costs by eliminating human interaction from a process. However, it was noted that AI implementations come at a high cost. Quality was viewed to have improved through better client experience, improved customer

insights, less human errors and 24/7 systems accessibility. It was also noted that poor data quality fed into AI systems can negate benefits achieved. The speed of operations processes was viewed to have improved through the automation of process. It was also noted that not all processes can be automated as some processes need discretion or empathy. Flexibility improvements were found to be around customisation of customer requests, product innovation and product mix. Dependability of operations services were improved through 24/7 systems availability, timely responses to clients as promised and internal SLAs.

As a result of this study, we now know the perceptions managers and employees have on the impact of AI to the operations performance of life insurance organisations in South Africa. There are no past studies that investigated the impact of AI in operations performance from the perspective of the manager or employee that has implemented and/or used AI technologies. This study has shed some light towards this phenomenon.

6.2 Limitations

The study managed to get 9 participants. The use of more participants may paint a better picture with more data on the impact of AI on operations performance.

6.3 Future Research

The study was limited to 9 respondents. A study involving more participants would add more value.

The study was made in the life insurance industry. It would be interesting if this study was simulated in other industries.

The study focused on qualitative methodology. It would be interesting to replicate the study using the quantitative methodology to see if the study would have similar findings.

6.4 Recommendations

Based on the reviewed literature and findings of this study, it is recommended that life insurance organisations must continue to apply AI technologies as a valuable resource to improve the performance of their operations and thus improve their competitiveness in the industry. A good understanding of AI technologies and their applications by people within the industry will influence stakeholder buy-in for AI projects.

AI technologies come with high upfront costs; therefore, it is recommended that companies that are interested in implementing AI applications not drive their uses cases solely based on cost reductions as they might not immediately realise cost benefits.

To have successful AI implementations, it is recommended that organisations do not use AI technologies to fix inefficiencies in processes. Inefficient processes must be fixed first before an AI implementation.

Also, it is recommended that bad data quality must not be used in AI technologies as they might lead to inaccurate predictions and a bad customer experience. Bad data quality issues must be resolved, or data must be cleaned first before being used by AI technologies.

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APPENDIX A: Research Instrument

Request to Participate:

We would like you to participate in this study through one-on-one interviews that will be made up of open-ended questions.

The participation will not be mandatory, and a participant may withdraw at any time.

Interviews Instructions:

Interviews will be scheduled at the convenience of the participant.

Interview Questions:

The interview questions will be centred around the implemented AI technology and the improvement in performance based on cost, quality, speed, dependability and flexibility.

The questions will be as follows:

1. What AI technology was implemented by the by the organisation?
2. On which process was the AI technology implemented?
3. When was the AI technology implemented?
4. What were the reasons or issues experienced before the AI implementation?
5. What were the improvements after the AI implementation?
6. Did AI implementation lower costs in the functional area?
 - a. What are these costs?
 - b. Can they be measured?
 - c. Can costs be compared based on before and after AI implementation?
7. Did AI implementation improve quality?
 - a. Is this product or process quality?
 - b. Can it be measured (for example by number of complaints or customer feedback)?

- c. Can quality improvement be compared based on before and after AI implementation?
- 8. Did AI improve the speed of product or service delivery to clients?
 - a. Can this be measured?
 - b. Can delivery speed be compared based on before and after AI implementation?
- 9. Did AI improve the dependability of products and services?
 - a. Can the timelines of products and services be measured (i.e. on-time versus late)?
 - b. Can timelines be compared based on before and after AI implementation?
- 10. Did AI improve the flexibility of operations processes?
 - a. Has the ability to change the production volume improved?
 - b. Has the ability to change product mix improved?
 - c. Has ability to cater for customised client requests improved?
 - d. Has the ability to innovate or introduce new products improved?
 - e. Can this flexibility be compared based on before and after AI implementation?