Factors Influencing Artificial Intelligence Adoption in South African Organisations: A Technology, Organisation, Environment (TOE) Framework

Master of Commerce in Information Systems

Research Report

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Declaration

I, Kaneez Fathima Hoosen, declare that this research report (Factors Influencing Artificial Intelligence Adoption in South African Organisations: A Technology, Organisation, Environment (TOE) Framework) is the outcome of independent research work conducted under the guidance of Professor Jason Cohen, for the fulfillment of the requirements of the Master of Commerce in Information Systems degree at the university of Witwatersrand.

I further declare that this research report has not been submitted, in whole or in part, for any other degree or diploma at any other university or educational institution.

Signature: ______________________ Date: _______________________

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Dedication:

I dedicate this research to my beloved baby, Zaeem. You are my greatest joy and inspiration. In these last few months, you have brought immense love, happiness, and purpose to my life. Your innocent laughter and support in your own special way has motivated me to push boundaries of knowledge and strive for excellence. Your presence has reminded me of the importance of making a positive impact on the world for future generations. May this research endeavour serve as a testament to my love and commitment to providing you with a better tomorrow. With all my heart, this work is dedicated to you, my precious baby.

ABSTRACT

Artificial intelligence (AI) refers to the formation of machines that mimic human intelligence and encompasses various technologies. AI technology is changing the landscape for South African organisations and how they operate.

Using current literature and other online reports by auditing firms, the study aimed to identify a suite of AI technologies used by South African organisations. Technologies such as robotic process automation, image and speech recognition, machine learning and chatbots were defined. In addition, this research paper investigated the factors influencing AI technology adoption by South African organisations. The technology, organisation and environment factors of the TOE framework were examined to understand adoption decisions. It was important to close this gap as lack of understanding of how factors influence AI decisions, and an undefined suite of AI technologies could impact adoption decisions.

A cross sectional relational research design was chosen for the study. A survey instrument was used and administered through a web-survey to 252 IT decision makers or IT leaders from South African organisations who served as key informants for their organisations. Responses were received from 55 organisations.

Reliability and validity tests were used to evaluate the consistency and reliability of the data and to evaluate whether measures correctly represent the variables that they intend to measure. Correlation analysis, stepwise and multiple regression were used to test the hypotheses of the conceptual model.

It was found that of the suite of AI technologies, robotics process automation followed by machine learning and image recognition had the highest levels of adoption. Results showed that data availability and top management support were supported as the most significant technology, organization, environment (TOE) factors influencing AI technology adoption in South African organisations. It was found that perceived technology benefits, IT infrastructure, resource capability and normative pressure were also strongly correlated to AI technology adoption. Financial resources and competitive pressure were not supported as determinants.

Artificial intelligence is receiving much attention in both practice and research. This study addresses the gap in the current body of knowledge on AI adoption in South Africa by making use of the TOE framework to study adoption of artificial intelligence technologies in organisations. Useful insights are provided to South African organisations so that they can benchmark their adoption against other industry players and manage their response to those factors most significant for AI adoption.

Keywords: AI, Artificial Intelligence, South African Organisations, TOE, Technology, Organisation, Environment, TOE Framework

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List of Abbreviations:

TOE	Technology Organisation Environment
AI	Artificial Intelligence
RPA	Robotics Process Automation
PCA	Principal Component Analysis
NLP	Natural Language Processing
IS	Information System(s)
IT	Information Technology
SLR	Systematic Literature Review

Chapter 1: Introduction

1.1 Background

Artificial intelligence can be broadly defined as the imitation of human intelligence practices carried out by machines or computers (Sheikh, Prins, & Schrijvers, 2023). A substantial amount of research is being carried out into the latest artificial intelligence (AI) developments (Access Partnership, 2018). The last few years have shown a growth in global interest from the financial, government, medical, agricultural and technology sector (Access Partnership, 2018). The capabilities of machines in recent times have expanded and according to the latest reports this trend will continue to grow (Saranya & Subhashini, 2023). Current investment in AI by organisations has been continuous according to the latest trends reported by Deloitte (Ammanath, 2022). South Africa is currently experiencing a decrease in economic growth with a high unemployment rate and low levels of skills, with overall competitiveness declining (Accenture, 2017). These are several challenges that AI may help solve. Accordingly, the different industry sectors have confidence that the AI can produce enormous benefits (Accenture, 2017). Questions are emerging into the adoption of AI and its value for organisations (Ammanath, 2022).

Artificial intelligence goes beyond process automation and is transforming the way that organisations operate and interact with customers (BCX, 2017). A Gartner report revealed that AI technologies such as voice recognition, machine learning and predictive analytics that bring about efficiency can be employed to develop products and services while at the same time reduce costs and processing times (Gartner, 2019). For example, a common challenge in the retail industry is establishing a process to keep track of goods and pricing data. Optical Character Recognition or OCR that uses natural language processing may be able to assist retailers with this challenge. OCR allows for a faster search process, quick editing and enables retailers to scan through a document to extract the correct information (Rizzoli, 2022; University of Pretoria, 2016). Another example is the manner in which AI based solutions may help financial institutions distinguish themselves from competitors by using chatbots and machine learning algorithms to enhance client relationship management (Deloitte, 2022). Apart from providing clients with good service, the algorithms can assist with identifying behaviour patterns, credit history and fraud detection allowing institutions to take a more proactive approach with servicing their customers (Deloitte, 2022). Applying these AI technology solutions can benefit organisations in various ways and improve security and transaction fraud detection in real time, relaying improvements on customer value and services (Pratt, 2021). A recent report by Mckinsey demonstrated an example of a cement company that wanted to improve their core assets. AI algorithms were used to create an optimizer to fine tune performance of their core assets. The results of the optimizer installation exhibited improvements in profits over a couple of weeks and established that AI algorithms or models can enhance the operation of the output, performance, and consumption of heavy machinery to increase profit (Charalambous, Feldmann, Richter, & Schmitz, 2019). These and other examples have influenced South African organisations to consider AI for increased customer service with use of a digital assistant, fraud prevention and predictive maintenance through use of pattern recognition and machine learning algorithms, smart manufacture, perceptive supply chains and intelligent lending solutions backed through data, among other uses (Gartner, 2019).

Yet South African industries are still implementing AI solutions in small pockets (Mckinsey, 2020), and despite the potential benefits described the rate of adoption of AI technology varies across South African organisations.

1.2 Problem Statement and Research Questions

The research problem can be summarized as lack of a distinctive definition of the suite of AI technologies that represent artificial intelligence in the South African industry and a lack of understanding of the extent to which these different technology, organisation and environmental (TOE) factors influence artificial intelligence adoption.

Artificial intelligence is a concept that is widespread. Previous research has not distinctively defined the types of technology that form the AI suite of technologies. Accenture and McKinsey describe the AI set of technologies as chatbots, machine learning, image recognition and robotics process automation (Accenture, 2017; Mckinsey, 2020). An undefined suite of AI technologies can impact a firm's decision to adopt AI. Practioners and organisations will find benefit with a well-defined suite of AI technologies as it can help them to make more informative technology investment decisions in the future (Hradecky, Kennell, Cai, & Davidson, August 2022). A necessity to distinguish the suite of technologies that represent artificial intelligence in the South African industry leads to the following research question:

RQ1: *What types of artificial intelligence technologies are used by South African organisations?*

A recent study conducted by Deloitte highlighted that companies such as Samsung, Google, Tencent and Apple have acquired over 100 start-up initiatives to promote AI, and this accounts for approximately 1 billion dollars (US) in technology investment (Van Buren, Chew, & Eggers, 2020). A McKinsey (2020) report revealed that revenue will increase by 46% by the year 2025 by organisations leading in the use of AI technology. Therefore, the pressure to lead the use of AI technology has increased for IT leadership in their organisations. Yet an Accenture 2019 study showed how some institutions often delay technology investments such as AI (Accenture, 2019). More research is needed to enhance the awareness and understanding of artificial intelligence in South African organisations, particularly, and to identify areas that organisations are lagging in as well as factors that have an effect on AI adoption. It was discovered in a

KPMG and Accenture survey that IT leadership acknowledged that only a small percentage of their current resources possess the required skillset to work on AI initiatives (Accenture, 2017; KPMG, 2020). This makes it difficult to respond to the pressure to adopt AI technology to augment competitive advantage. Furthermore, other organisational challenges exist such as quick implementation strategies and compatibility with existing technology infrastructure and data (AnalyticsWeek, 2020). There is currently a lack of understanding of the extent to which these different technology, organisation and environmental (TOE) factors influence artificial intelligence adoption in South African organisations. Hence, this research study will also address the present gap in the current body of knowledge about aspects that could impact adoption of AI technology in the South African industry. This leads us to the following research question:

RQ2: *What TOE factors influence adoption of AI technology in South African organisations?*

- ***RQ2a**: What technology factors influence adoption of AI technology in South African organisations?*
- ***RQ2b**: What organisational factors influence adoption of AI technology in South African organisations?*
- ***RQ2c**: What environmental factors influence adoption of AI technology in South African organisations?*

1.3 Purpose of the Study

To address the research questions, this paper focuses on identifying the applicable types of AI technology and identifying the factors that influence South African organisations to adopt AI technology. Moreover, research requires an AI adoption model to be developed and tested using data collected from a sample of organisations. The TOE framework will be applied as a lens to develop the model (Chapter 3) and provide an empirical study that will assess the factors that affect South African organisations adoption of artificial intelligence.

The objectives of the study are:

- Identify the types of AI technology available for adoption by South African organisations by evaluating current literature and through input of experts.
- Evaluate past TOE literature to develop a comprehensive research model to study the factors that influence AI adoption in South African organisations.
- Gather data from the selected sample of organisations in South Africa through the use of a survey methodology.
- Use correlation and regression analysis of the data to test the model.
- Provide a foundation for future research studies that want to contribute and expand the understanding of factors of AI technology adoption on an organisation level.

1.4 Intended Contribution of the Study

1.4.1 Contribution to theory:

There are limited studies that use quantitative methods to study information systems and technology adoption, especially AI. This research report utilizes the technology, organisation, and environment (TOE) framework as a theoretic lens to study artificial intelligence adoption by organisations. Using the TOE framework in the study highlights the gaps in IS research as the TOE framework has not been used extensively as a tool to study AI adoption (Mariemuthu, 2019). The literature highlighted later in the study will show that the TOE framework was used in adoption studies for cloud computing, RFID, e-commerce systems etc. (Bhattacharya & Wamba, 2015; Gutierrez, Boukrami, & Lumsden, 2015). However, only a few studies were found that used the TOE framework to study AI technology. The TOE framework has been used in many studies; however, the factors of technology, organisation and environment differ across technologies (Baker, 2011).

Diffusion of innovation theory suggests technology factors should impact technology adoption and diffusion (Rogers, 1995). Data availability as a technology factor has not been considered in past literature on artificial intelligence adoption. This research report will address this gap by examining data availability as a technology factor. However, the importance of such technology factors to AI adoption has not been established, especially in relation to other factors such as organisational or environmental factors. For example, competitive pressure is popularly presented as an environmental factor contributing to technology adoption (Shi, Shambare, & Wang, 2008). However, the influence of competitive pressure has not yet been established for AI adoption. Accordingly, the highlighted potential of AI technology poses a need for an all-inclusive view of the TOE framework factors influencing adoption. This study will contribute to the unpacking of variables with use of a theoretical model to highlight the relevance of different factors on AI adoption decisions.

1.4.2 Contribution to practice:

The research report will contribute to practice by identifying the types of AI technology used by South African organisations. Robotics Process Automation, Machine Learning, Chatbots are a few AI technologies (Deloitte, 2021). However, South African industry players may lack understanding on which are the most significant AI technologies available for adoption, or how they should invest or develop internal skills or respond to factors that may be important to their adoption.

Effective adoption of AI technologies is likely to benefit South African organisations, supporting them to remain competitive against industry players who disrupt their industry. For example, reports have shown that fintech organisations are using AI technology to reduce their costs and provide more affordable products to customers (Broby, 2021). Organisations that adopt AI technology will be likely to reap the rewards of increasing their customer footprint, develop cost effective products and services in a timeous manner (Accenture, 2019). Lastly, the results produced in this study can generate insights and valuable lessons on the TOE factors most relevant to adoption and thereby assist organisations to better prepare for AI adoption.

1.5 Delimitations of the Study

- The study is an organisational level study with emphases on business areas in South Africa. It will not focus on individual level adoption by employees or on adoption of AI by customers.

- The study will limit itself to focusing on organisations operating in financial, retail, manufacturing, and related sectors in South Africa. Further studies are encouraged to focus on other sectors such as agriculture or medicine and other developing countries.

- The study uses the TOE framework and variables from institutional (DiMaggio and Powell, 1983) and diffusion of innovation theory (Rogers, 1995). While the framework is considered as a strong adoption framework for firm level adoption, it does not provide the practice of studying an organisation over a period of time and thus limits an opportunity for a longitudinal study.

- The research is deductive in nature and utilises the TOE framework and previous studies for the development of the research model. Fundamentally, factors not postulated, and a-priori incorporated in the research model will not be studied.

1.6 Report Structure

Chapter One:

The first chapter of the report provides an introduction and background to artificial intelligence. It highlights the research problem and questions being investigated and touches on the contribution to practice and academia.

The rest of the document is divided as follows:

Chapter Two: Literature Review

Chapter two unpacks the systematic literature review which provides a foundation to answer Research question one by analyzing the types of AI technologies in South African organisations. Past research studies using the TOE framework for technology adoption are also reviewed in this chapter.

Chapter Three: Theoretical background and research model

The underpinnings of the TOE framework are discussed in chapter 3. The conceptual model for the research study is also further developed with the eight hypotheses formulated.

Chapter Four: Research Methodology

The pre-test and pilot test results are discussed in this chapter. An overview of the quantitative research design used to answer RQ1 and 2 is provided.

Chapter Five: Research Findings

Chapter five delivers a summary of the findings of the research study. The focus of this chapter will be to organize and present the data collected for the study.

Chapter Six: Discussion of Results

In this chapter, the findings from chapter five will be discussed in detail and the significance of the research findings will be highlighted.

Chapter Seven: Conclusion

This chapter ties together the discussion of results, the limitations of the study and suggestions for future research.

Appendices

The appendices contain the pretest, pilot test summaries as well as the final survey, cover letter and ethics clearance certificate.

Chapter 2: Literature Review

The literature review presents an overview of the current literature that studies the types of artificial intelligence (AI) technologies and the TOE framework used in adoption studies. A systematic literature review (SLR) is also developed in this chapter. The SLR aimed to define the types of AI potentially relevant to South African organisations, to address Research question one.

2.1 Artificial Intelligence (AI) Defined

Artificial intelligence is not a new concept and has been around since the 1950's. The term was coined by scientist John McCarthy (Anyoha, 2017). Although the start of the AI journey faced many challenges, it is a field that flourished over the years and became widely known to industries across the globe (Anyoha, 2017).

Several definitions of artificial intelligence exist. In this study, AI will be defined as a constellation of technologies allowing machines to behave with superior levels of intelligence, imitating human capabilities such as sensing, understanding, and acting (Access Partnership, 2018). These capabilities are improved by the ability of the machine to learn and adapt from experiences over-time (Access Partnership, 2018).

Billions of dollars (US) have been invested in artificial intelligence technology start-ups by organisations, providing artificial intelligence technology applications to clients and the broader market (Deloitte, 2021). AI as an innovation has provided efficiency and simplicity to people's jobs by taking away mundane tasks that can be automated (Boitnott, 2020). Some of the advances of AI technology that enhances the use of digital machines are audio processing, predictive analytics, natural language processing and image recognition (Kovalenko, 2021). These advances allow machines to understand and form conclusions on the data collected and to gain experience for future interactions (Accenture, 2017). The next section below will discuss the various types of AI technologies and show its relevance to this research.

2.2.1 The Types of AI Technologies

The purpose of the systematic literature review was to address research objective one which was to gain an understanding of the existing literature and to identify other AI technologies that should be explored in this research paper. This study will critically assess the articles found through the electronic database search and synthesize the findings to answer Research question one.

A systematic literature review is a rigorous and comprehensive method used to identify, evaluate, and synthesize all the available evidence related to a specific research question or topic. The steps highlighted in table 2.1 below were adapted from Okoli (2015).

Literature Review Steps	Description and Purpose
1. State the purpose of the literature review and the research question	To understand the existing body of knowledge for Artificial Intelligence and adoption. The systematic literature will provide a foundation to answering the research question.
2. Identifying electronic databases	Identify electronic databases that store research papers from the highest ranked IS journals.
3. Search for the literature	Explain the details of the systematic literature review search as well as the search criteria used.
4. Practical Screening	Inclusion and exclusion criteria identified and listed.
5. Extraction of data and synthesis	Scientifically analyze the data and extract the relevant information for the study.
6. Report the findings	Report the findings concisely so that the SLR can be replicated.

Table 2. 1: SLR Steps

Step 1:

The purpose of the systematic literature review was to understand the types of AI technologies that could be used by some South African organisations.

Step 2:

The databases identified for the review were selected using the following criteria:

- Contains peer reviewed articles from reputable IS Journals (2014-2023)
- Conference and proceeding journals
- Advanced search options available
- Database available through Witwatersrand library account
- Full text articles were easily accessible

The following database engines were utilised for the systematic literature review:

- SpringerLink
- Science Direct
- Scopus
- ProQuest ABI/INFORM Collection

Step 3:

In reference to the SLR methodology, the following were utilized to construct the search strings:

a) Unit of analysis:

- South African Organisation OR

- South African Organization OR
- South African Company OR
- South African Industry

b) IT artefact:

2.2.1.1 Artificial Intelligence OR

2.2.1.2 AI Technology

c) Phenomenon of interest:

2.2.1.3 Category

2.2.1.4 Type

2.2.1.5 List

List of search strings that were used:

- South African Industry AND Artificial Intelligence AND Category
- South African Industry AND Artificial Intelligence AND Type
- South African Industry AND Artificial Intelligence
- South African Industry AND AI Technology AND Category
- South African Industry AND AI Technology AND Type
- South African Industry AND AI Technology
- South African Organisation AND Artificial Intelligence AND Category
- South African Organisation AND Artificial Intelligence AND Type
- South African Organisation AND Artificial Intelligence
- South African Organisation AND AI Technology AND Category
- South African Organisation AND AI Technology AND Type
- South African Organisation AND AI Technology
- South African Organization AND Artificial Intelligence AND Category
- South African Organization AND Artificial Intelligence AND Type
- South African Organization AND Artificial Intelligence
- South African Organization AND AI Technology AND Category
- South African Organization AND AI Technology AND Type
- South African Organization AND AI Technology

Step 4:

To ensure the selected articles met the required quality standards for the study, the following criteria were employed for inclusion and exclusion purposes:

a) Inclusion criteria

2.2.1.6 Articles that were on an organisational level

2.2.1.7 Studies that contained quantitative research methods

2.2.1.8 Studies that contained qualitative research methods

2.2.1.9 Practitioner-based research

2.2.1.10 Research papers from conferences and journals

2.2.1.11 Articles in the English language for the purpose of reading and analyzing.

2.2.1.12 Studies based on South African Organisations

2.2.1.13 Studies that were published in the last nine years (2014-2023)

b) Exclusion criteria

2.2.1.14 Individual-level study

2.2.1.15 Articles that were not in English

2.2.1.16 Artificial Intelligence studies that are based on the medical industry.

Step 5:

With reference to Research question one and the gap that was identified with the existing literature, 11 studies were identified that fulfilled the inclusion and exclusion criteria.

Step 6:

The review of the studies is shown below in two parts. The first part of the review unpacks AI adoption examples in organisations and the second part demonstrates AI adoption in organisations and the framework that was used to measure adoption.

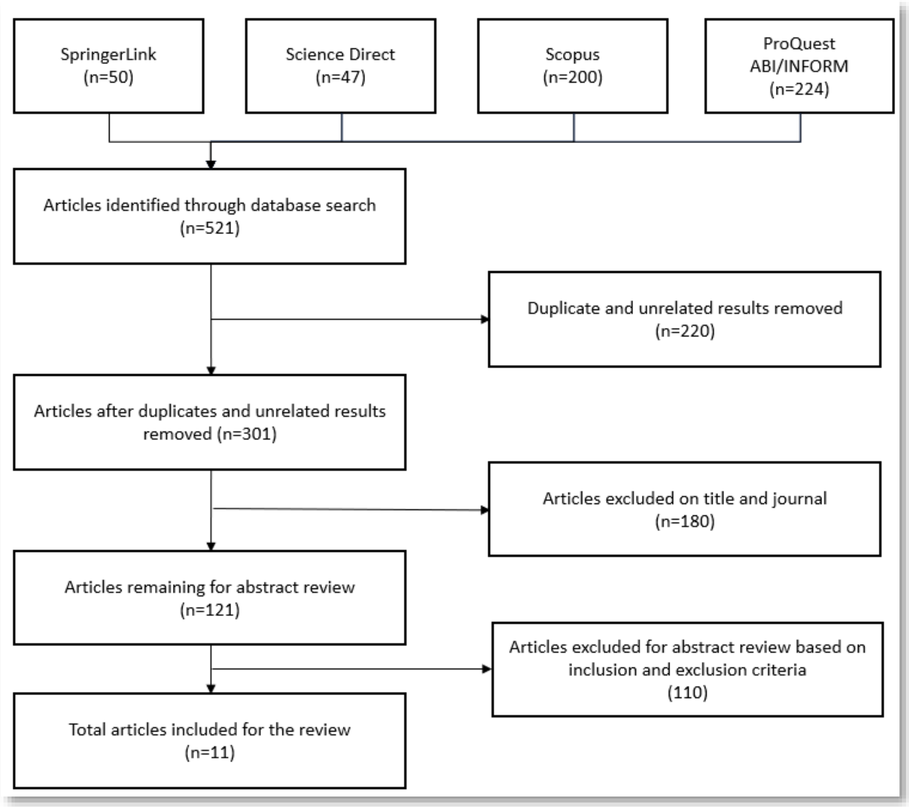

Figure 2. 1: Systematic literature review for AI adoption in organisations

Reference	Speech Recognition	Chatbots | Virtual Assistants	Image Recognition	Robotics Process Automation	Machine Learning	Natural Language Processing	Neutral Networks
(Hradecky, Kennell, Cai, & Davidson, August 2022)	✓	✓		✓			✓
(Alhawti, 2015)					✓		
(Cao, Duan, Edwards, & Dwivedi, August 2021)					✓		✓
(Grguric, Vlacic, & Drvenkar, 2020)						✓	
(Milojevic & Redzepagic, 2021)					✓		
(Gal, Gallina, Szaller, & Schlund, 2023)				✓			
(Tsuchiya, Hatano, & Nishiyama,			✓			✓	

2023)							
(Benbya, Davenport, & Pachidi, 2020)				✓	✓	✓	✓
(Ammanath, 2022)				✓	✓		✓
(Kabalisa & Altmann, 2021)	✓		✓		✓	✓	
(Benbya, Pachidi, & Jarvenpaa, 2021)		✓		✓			

(Source: Researcher's own compilation)

The next section will discuss types of AI technologies.

2.2.2 Types of AI Technologies and their Application

Research and analysis of the literature was carried out to understand the different types of AI technologies that exist and how it is applied in South African organisations. Over the years, the group of technologies that were popularly related to AI are recognised as significant contributors to innovation in numerous industries (Access Partnership, 2018). Advancement of robotics process automation (RPA), machine learning, chatbots, and natural language processing (NLP) are all AI technologies that are making a significant stride by improving service and product offerings of organisations (Ammanath, 2022; Access Partnership, 2018).

Customer account data, credit information, transaction history and other supply chain information are all types of data produced by organisations (Castelli, Manzoni, & Popovic, 2016). Hidden patterns that exist in the data that are valuable can be discovered (Benbya, Davenport, & Pachidi, 2020; Deloitte, 2021). Some challenges organisations are dealing with today are fraud risk, increased costs, loss of customers and risk avoidance (Deloitte, 2021). It has become increasingly important for organisations to use their data to discover important insights that will help them mitigate fraud, retain their consumers, and avoid unnecessary risk. AI algorithms comb through millions of data points to identify patterns that are not visible to humans (Accenture, 2019). One bank, HSBC, is using machine learning to detect money-laundering cases. Machine learning technologies can spot abnormalities in data and envisage cases in which regular transactions do not fit the "mould" (Access Partnership, 2018). In a recent Fintech report, Deutsche bank has partnered with Google to use their machine learning technology to drive their strategic goal of protecting their clients and growing their business (Villar & Khan, 2021). Business leaders across industries have realised the value of data during the Covid pandemic (Mckendrick, 2021). Plans of building a foundation for data within organisations have accelerated as leaders understand the powerful insights received from data algorithms to assist in heightening their business ventures, providing agility to procedures and processes, learning about their customers, and creating new business streams (Mckendrick, 2021; Cao, Duan, Edwards, & Dwivedi, August 2021). The manufacturing industry uses machine learning for predictive maintenance as it can anticipate equipment failure or when maintenance is required (Zhydik, 2021).

As organisations are becoming more technologically advanced, competitiveness amongst industry players have increased as more industries want to provide products that are innovative at a faster speed and lower cost (Mckendrick, 2021). However, organisations do face the complexity of legacy infrastructure and systems and are not immediately flexible when it comes to big technology changes (Shim, 2019) . RPA is an AI technology that uses algorithms to automate monotonous tasks that are typically mundane and prone to human error (Benbya, Pachidi, & Jarvenpaa, 2021; Dirican, 2015). Pre-populating of structured data forms to increase processing speeds is assisting organisations to focus on providing superior customer service. The introduction of RPA in organisations can assist businesses to be more available to service customer needs (Gal, Gallina, Szaller, & Schlund, 2023; Dirican, 2015).

Natural language processing (NLP) is used by machines to recognize and evaluate human language. The retail, manufacturing, and financial industry use NLP to improve customer interactions by using a chatbot to assist with simple queries (Alhawti, 2015). Overtime, the system learns to resolve different queries automatically without human intervention. Ask Alexa is being used in Amazon fresh stores to assist customers to find products in the store (Waters, 2021). Other retail service providers like McDonalds are also adopting virtual assistants to help customers order food (Waters, 2021). Bank of America used their chatbot Erica to resolve over 175 million queries or requests for 15 million clients since she launched in 2020 (Schwartz, 2021).

A neural network comprises of interconnected AI neurons or nodes that are arranged in layers (Benbya, Davenport, & Pachidi, 2020). Neural networks are widely used in various industries. Companies are using neural networks to understand customer purchase behaviour, analyzing credit scoring for loan applications, transportation routes etc. (Ammanath, 2022). The logistics industry has adopted neutral networks to plan, monitor, and customize routes in real time (Pruciak, 2021).

Formulated through the systematic literature review, Table 2.2 below describes the types of artificial intelligence technologies. Promising examples of AI Technology and their use cases within South African organisations are also provided.

The purpose of the systematic literature review was to address Research question one by defining a suite of AI technologies relevant to South African organisations. The response to Research question one is summarized in the below table.

Type of AI technology	Definition	Example of use in Organisations
Speech Recognition	Speech recognition refers to the capability of a machine or application to recognise human speech and transform the words into comprehensible text (Alhawti, 2015).	The financial, retail and manufacturing industries are investigating the use of voice recognition AI technology to improve resolution of customer queries and streamline manufacturing. The AI voice application will effortlessly confirm the identification of customers when they dial into call centres (Alhawti, 2015). Speech recognition technology was identified by BSH to resolve their bottleneck, where employees were struggling to manage their assembly line. The voice recognition technology adopted by BSH assisted employees to streamline their assembly line with minimal manipulation, resulting in cost savings for the company (Tomar, 2021).
Chatbots or Virtual Assistants	A virtual assistant is an application designed to enhance communication between humans and their application of use. Virtual assistants use natural conversation to provide customised advice or help to consumers (Hradecky, Kennell, Cai, & Davidson, August 2022; Stoeckli, Dremel, Uebernickel, & Brenner, 2020).	McDonalds has taken the lead in the retail industry and introduced virtual assistants in their hiring process. Job seekers will access the technology via their Google assist or Amazon’s Alexa. The virtual assistant will find open positions at McDonalds in the user’s country of choice (Durbin, 2019). Bank of America’s “Erica” makes transferring money a seamless task. Erica uses voice activated services on

		your mobile or PC to help the customer transfer money, essentially saving the customer time on day- to-day banking transactions (Schwartz, 2021).
Image Recognition	Image recognition denotes the capability of applications to identify items, places, or individuals through features in the image (Kabalisa & Altmann, 2021; Mariemuthu, 2019).	The financial industry is using facial recognition technology to enhance customer security. Online financial applications are using biometrics to authenticate customers identities (Tsuchiya, Hatano, & Nishiyama, 2023; Kovalenko, 2021). FaceMe, a facial recognition technology, has become one of the leading technologies in the retail sector. Adoption of FaceMe has increased during the Covid-19 pandemic as more retailers required a wider forecast of client behavior, purchasing habits and demographics. The data collected from using this technology was able to enhance efficiency and flow, resulting in savings and greater competitor advantage (FaceMe, 2022).
Robotics Process Automation (RPA)	RPA being a subset of artificial intelligence, is a software robot that is designed to perform business processes governed by specific rules that mimic human interactions (Ammanath, 2022).	In the manufacturing industry, RPA-driven parts rationalization is used to create efficiency in the manufacturing and engineering process by identifying designs that are similar. This decreases material costs as increased volumes are sourced with a smaller number of designs (Deloitte, 2022).

Machine Learning	Machine learning represents a subset of artificial intelligence providing self- learning capabilities to computers and systems to adapt and improve through experiences without the need for explicit programming. The key objective of machine learning is for the machine to spontaneously learn from patterns and datasets (KPMG, 2020; Donepudi, 2017).	TymeBank, a digital only bank in South Africa has made great strides with using machine learning algorithms. As of November 2018, the bank gained 670 000 customers. TymeBank uses machine learning to improve fraud detection by enhancing their bank surveillance technology to understand common drivers that determine fraudulent activity. Another common usage of machine learning is to recognise information from multiple feeds and segments thus making a great tool for credit scores (Malinga, 2019). The manufacturing industry uses machine learning to predict energy usage and monitor factors such as temperature, activity levels and lighting. This helps factory managers to plan for their future consumption needs (Zhydik, 2021).
Neural Networks	Neural networks are a form of computational simulation. It is inspired by the formation and function of the human brain. The various layers of neurons process and transmit information (Benbya, Davenport, & Pachidi, 2020).	Neural networks are used in speech, image, NLP, and predictive analytics. Google self-drive car, Waymo is an example of neural networks. Waymo uses a combination of NLP, speech, and image recognition as well as deep learning to identify objects such as animals, obstacles, and markings on the road to make the journey safer. (The Guardian, 2022).

Table 2. 2: Types of AI Technology and organisational example

2.3 AI Adoption at an Organisational Level

This section covers a review of past empirical studies of AI adoption which addresses research objective two. Research papers that were selected had to fall within the following categories: studies that were in the year range of 2014 – 2023, based on AI in organisations excluding the medical industry, peer reviewed articles and both qualitative and quantitative studies.

Kabalisa & Altmann (2021) paper explores the economic impact of artificial intelligence adoption on countires and organisations over the past four years i.e. 2018 -2021. The literature review was made up of research papers that identified organisations in developing countries that used diverse AI technology. Some of the industries identified in the study as being impacted by AI adoption were the automative, manuafacturing, banking, logistics and healthcare industries. Most industries highlighted that their reasons for AI adoption are market pressure, positioning themselves as leaders, growth, efficiency, productivity and competition (Kabalisa & Altmann, 2021).

The various theoretical frameworks used to study AI adoption was investigated in Radhakrishnan & Chattopadhyay (2020). The most used adoption theories that were emphasised in the paper were TOE and DOI for organisational level studies and for individual level studies UTAUT and TAM. Some of the barriers to AI adoption they identified were system downtime, privacy breaches, job loss for both employees and management. Alsheibani, Cheung, & Messom (2018) investigated AI readiness using a mixed methods approach. Their objective was to propose a framework based on the TOE and DOI theoretical frameworks that examines readiness for AI adoption at organisational level. A similar study examining AI readiness by Small and Medium Enterprises (SMEs) by Bettoni et al. (2021) proposes a model to measure AI adoption readiness for SMEs. The objective of the model is to consistenly measure maturity level of adoption across SME's. The factors that were used are human resources, data strategy, organisational structure and culture (Bettoni, Matteri, Montini, Gładysz, & Carpanzano, 2021)

Managers behavioural attitude and decision making towards using AI was investigated in a research paper by Cao et al, 2021. A new research model called IAAAM which is a combination of UTAUT and TTAT was conceptualised in the study. UK managers in the private sector was used as the sample population for the study. Favourable conditions such as skills training, equipped environment and peer influence contibuted positively to managers decision making. Personal concerns was seen to negatively affect managers decision making (Cao, Duan, Edwards, & Dwivedi, August 2021). Fintech's were examined from a resource optimization view in a study by Almansour (2023). The research aimed to close the gap on the usage of resources after AI technology was adopted. Physical resources such as office space, stationery and fuel were reduced. Fintechs realised benefits such as increased time and availabiliy of human resources to assist with enhancing the client experience

(Almansour, January 2023).

AI readiness in the Western Europe exibition sector was explored by Hradecky et al., (2022). The TOE framework and Technology Readiness Index (TRI) was used in the study to understand AI adoption readiness. The study revealed that AI adoption depends on an organsations IT infrastructure as this provides increased potential for optimisation benefits. Secondly organisation size plays a role in rate of adoption. For example, a small firm may adopt AI technology faster than a larger sized organisation as they may have a smaller group of stakeholders to gain buy-in from (Hradecky, Kennell, Cai, & Davidson, August 2022).

The developing landscape of AI technology in the South African construction industry and the factors that influence organisation adoption in developing countries were evaluated by Tjebane et al., (2022). Factors that were investigated in the study are government pressure, competitive pressure, cost and time saving and work relationships amongst employees.

Useful evidence from these studies suggest that TOE framework is a significant framework to study the adoption of a technology. Table 2.3 below displays a summary of the findings from AI adoption studies in organisations and illustrating that a comprehensive set of TOE factors has not been explored.

Research Study	Technology Studied	Key Findings and Variables
AI Technologies and Motives for AI Adoption by Countries and Firms: A Systematic Literature Review (Kabalisa & Altmann, 2021)	Artificial Intelligence	This study concentrated on the economical impact of AI adoption in organisations. Variables examined were: • Productivity, increasing income, competitiveness, and creation of value.
An AI adoption model for SMEs: a conceptual framework (Bettoni, Matteri, Montini, Gładysz, & Carpanzano, 2021)	Artificial Intelligence	This research study produces a conceptual framework to encourage artificial intelligence adoption in SMEs. Variables examined were: • Under-skilled employees • Complexity of solutions • Data availability
Artificial Intelligence Adoption: AI-readiness at Firm-Level (Alsheibani, Cheung, & Messom, 2018)	Artificial Intelligence	The objective of the study was to identify factors that impacted organisational readiness of AI adoption. Variables examined were: • Relative advantage • Technology readiness • Firm size • Compatibility
Organisational Factors of Artificial Intelligence Adoption in the South African Construction Industry (Tjebane, Musonda, & Okoro, 2022)	Artificial Intelligence	Adoption of AI technology was investigated in the South African construction industry. Variables examined were: • Performance and Risks involved with AI technology • Collaboration and Top management support • Cost, culture, and employee relationships
Determinants and Barriers of Artificial Intelligence Adoption – A Literature Review (Radhakrishnan & Chattopadhyay, 2020)	Artificial Intelligence	Barriers, determinants, and the most common theoretical frameworks were looked at in this study. Variables examined were: • Intrinsic motivation • Customer needs • Infrastructure • Culture and prior experience

Table 2. 3: Summary of AI adoption studies

2.4 Conclusion: Chapter Two

The need for a systematic literature review existed to identify other AI technologies that should be explored in the research. This provided a provisional answer to Research question one. What types of artificial intelligence technologies are used by South African organisations? The literature review suggested speech recognition, chatbots and virtual assistants, image recognition, robotic process automation, machine learning, and neural networks are relevant AI technologies for further exploration. In addition, past studies emphasized the significance of the TOE framework in IT adoption studies. Although TOE framework was used to study AI adoption in organisations, not all potentially relevant constructs have been considered in past studies. Chapter three discusses the foundation of the TOE framework and formulates the conceptual model aimed at addressing Research question two. What TOE factors influence adoption of AI technology in South African organisations?

Chapter 3: Theoretical Background and Research Model

The purpose of this chapter is to outline the theoretical background and research model needed to address Research question two, what TOE factors influence adoption of AI technology in South African organisations? Several theoretical frameworks exist for technology adoption in information systems research. Some of these frameworks are technology acceptance model (Davis,1986), diffusion of innovation theory (DOI) (Rogers, 1995), institutional theory (DiMaggio & Powell, 1983), theory of planned behaviour (ajzen,1985), unified theory of acceptance and use of technology (Venkatesh et al, 2003) and technology-organisation- environment framework (Tornatzky and Fleischer, 1990). The technology acceptance model, theory of planned behaviour and unified theory of acceptance and use of technology frameworks are usually associated with individual level studies and are established in sociology studies. The TOE framework, DOI and institutional theory have been linked with studies pertaining to organisational level adoption.

3.1 Technology Organisation Environment (TOE) Framework

The TOE framework was established in 1990 by Tornatzky and Fleischer. The framework provides a lens to study technology and innovation adoption on an organisational level. The framework identifies three elements that influences an organisations decision to adopt a new technology (Oliveira & Martins, 2011). The three elements are technological, organisational, and environmental context (Baker, 2011). All three elements are considered to influence technology innovation and the method that organisations adopt when considering new innovations or technology (Baker, 2011; Oliveira & Martins, 2011). Figure 3.1 shown below represents the TOE framework and the elements mentioned above.

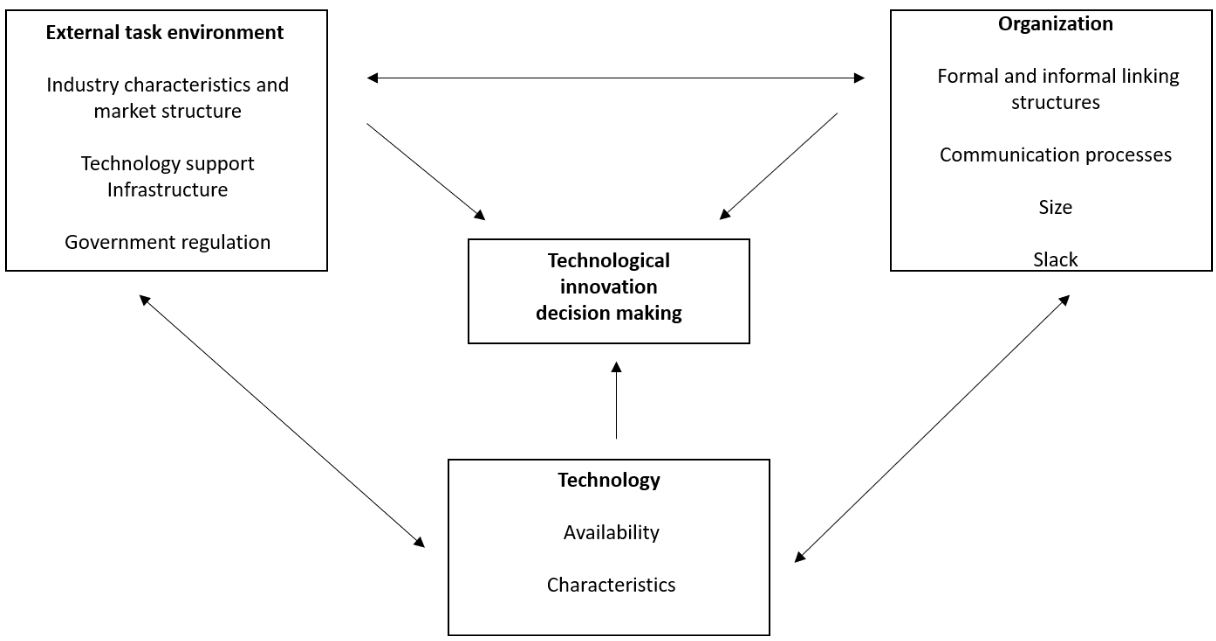

Figure 3. 1: Technology Organisation Framework

(Source: Tornatzky and Fleischer, 1990)

The study will use variables from diffusion of innovation theory (DOI) and institutional theory. The DOI theory is widely used to explain adoption patterns (Rogers, 1995). The theory focuses on the how, why and the what of new innovations and ideas that are built through cultural norms at an individual or organisational level (Park & choi,2019). Innovation at an organisational level comprises of a few individuals, more commonly including both followers and opponents of the innovation. All these individuals will have a role to play in the innovation decision. Institutional theory focuses on understanding management and organisational practices through a social lens rather than with a lens of economic pressure (DiMaggio & Powell, 1983).

3.1.1 TOE Framework - Technology

The technology aspect of the framework incorporates all technologies relevant to the organisation. This includes technology that is currently in use as well as technology available in the market (Baker, 2011). Current technology available in the organisation should be viewed as a benchmark for new technology adoption as it defines the limitation of the type and speed of the technological revolution and journey that an establishment can accommodate. Technology available but not in use by the organisation influences adoption through the limits established by what the organisation can accomplish and by presenting how the technology can aid in attaining their objectives (Baker, 2011). IT infrastructure, IT capability and perceived benefits are technological factors that are considered relevant (Mariemuthu, 2019). Research has shown that firms with superior IT infrastructure are more likely to be successful with technology implementations (Accenture, 2019). Firms with highly experienced technical resources and expertise were found to develop more innovative technology (Mckinsey, 2020).

3.1.2 TOE Framework - Organisation

The organisational aspect of the framework highlights the organisations characteristics, resources, firm size, and internal communication processes within the organisation (Baker, 2011). Various studies show how the organisational aspect of TOE framework influences adoption. Technology readiness in the research paper by Oliveira and Martins (2010); perceived technical competence by Chen, Li, & Chen (2021); and top management support and resource capability by Bhattacharya & Wamba (2015). Senior IT managers can take the initiative of fostering innovative ideas and digital change that can develop the firm’s vision and strategy (Gartner, 2019). Resource capability and organisational support are usually considered as relevant factors for the organisational context.

3.1.3 TOE Framework - Environment

The environmental aspect of the TOE framework elaborates on the industry structure, regulatory players, technology service providers and other factors such as customer demand or behaviour that may influence an organisations adoption behaviour (Baker, 2011). The factors mentioned can directly or indirectly mold an organisations strategy towards innovation (Oliveira & Martins, 2011).

Studies suggest that organisations that are in fast growing environments will innovate more than organisations that are in mature or declining environments (Accenture, 2019; Baker, 2011). However, some declining or mature organisation may use the opportunity to innovate to re-establish their place in the market. Competition in the industry also boosts adoption of new technologies (Baker, 2011).

Highly driven technology sectors are often related with making swift changes as these types of organisations face pressure from other competitor firms and have become more aware of adopting the latest technologies (Duh & Fabiao, 2018). Mimetic and coercive pressure are considered as relevant factors for the environmental context.

Research Study	Technology Studied	Key Findings and Variables
The Adoption of Artificial Intelligence by South African Banking Firms: A Technology, Organisation and Environment (TOE) Framework (Mariemuthu, 2019)	Artificial Intelligence	Mariemuthu, (2019) focused on the current state of adoption of AI in the banking context and examined the following variables; “Technological – Perceived benefits, IT Infrastructure, AI Technology skills Organisational- Top management support, Firm size, Cost Environmental - Legal requirements, Mimetic, and competitive pressure”
Organizational and market factors affecting mobile banking adoption by Mozambican banks (Duh & Fabiao, 2018)	Mobile Banking	A key finding was that vendor support had the highest effect. Other variables such as customer, competitive pressure and financial resources was also found to impact adoption. Variable examined were: • Organisational -Top management support, financial resources, employee capability • Environmental - Vendor support, competitive and customer pressure

Technological, organisational and environmental factors influencing managers' decision to adopt cloud computing in the UK (Gutierrez, Boukrami, & Lumsden, 2015)	Cloud Computing	An important aspect of the study was that trading partner pressure was the most significant factor that influenced adoption. Variables examined were: • Technological - Relative advantage, complexity, compatibility • Organisational - Top management support, Firm size, Tech readiness • Environmental - Competitive/trading partner pressure
A Conceptual Framework of RFID Adoption in Retail Using TOE Framework (Bhattacharya & Wamba, 2015)	RFID	Variables examined were: • Technological – Relative advantage, cost, complexity, compatibility • Organisational – Top management support, size, IT expertise • Environmental – Catalyst agent, external support, competitive pressure Relative advantage, catalyst agent and value chain complexity were found to be significant factors of RFID adoption.
Explore success factors that impact artificial intelligence adoption on telecom industry in China (Chen, Li, & Chen, 2021)	Artificial Intelligence	Key findings were: • Managerial capability directly influences adoption. • Market uncertainty and competitive pressure were not positively related to AI adoption. Variable examined were:

		• Technological – Complexity, relative advantage, compatibility • Organisational – Managerial Capability, technical capability • Environmental – Market uncertainty, competitive pressure, government involvement
Firms Patterns of E-Business Adoption: Evidence for the European Union-27 (Oliveira & Martins, 2010)	e-business	Key findings: • TOE factors were impacted most by firms with greater levels of e-business. • Competitive pressure was found to be a driver for adoption in corporate firms. • The technology factor impacts manufacturing more than the tourism industry. Variables examined were: • Technology - technology readiness; technology integration • Organisational - firm size • Environment - competitive pressure and internet penetration
Reasons for information technology adoption and sophistication within manufacturing SMEs (Ghobakhloo, Benitez-Amado, & Aranda, 2011)	Information Technology	Variables examined were: • Technological – Information processing capacity • Organisational – IT enabled-organisational improvements. • Environmental – Environmental/ competitive pressure

		External pressure was found to be the most significant factor.

Table 3. 1: Past studies that used the TOE Framework

3.2 Research Model and Hypotheses

To address Research question two, the TOE framework was adopted to develop a contextual research model of artificial intelligence adoption by South African organisations. There are eight independent variables that form the TOE framework factors that were hypothesised to influence artificial intelligence adoption by organisations. TOE offers a general model; researchers need to select a precise set of factors that complement the TOE framework (Oliveira & Martins, 2011). This study included factors from the DOI and institutional theory frameworks to strengthen the adoption argument. This is shown below in figure 3.2, the conceptual framework for factors that influence South African organisation adoption of artificial intelligence.

3.2.1 The Technology Organisation Environment (TOE) framework and adoption of AI

Numerous empirical studies using the TOE framework were identified and analysed as shown in Table 2.2 above. The TOE framework was argued to be robust in displaying its usability for technology or innovation adoption across industries. The framework was used to describe mobile banking adoption by Mozambican banks (Duh & Fabiao, 2018), Cloud computing adoption in the UK (Gutierrez et al., 2015), RFID adoption in the retail industry (Bhattacharya & Wamba, 2015) and AI adoption in the Chinese telecom industry (Chen, et al., 2021). Technologies that used the TOE framework as a lens are open systems, e-commerce, cloud computing, ERP systems, and RFID’s.

The evaluation of the literature revealed that several studies that used the TOE framework were quantitative and were at an organisational level. A collated view of the studies suggest that the TOE framework is suitable for organisational level study and to study adoption of a technology. The research studies mentioned have supported in creating a foundation for developing a research model to study adoption. Notable factors from the studies were established to drive the adoption of AI technology. The lesson taken from the studies mentioned is that the TOE framework is well-structured and established, has been used in many adoption studies over the years and is a valuable lens to study a diverse range of innovative technologies. Taking into consideration the theme of this research paper, the TOE framework will be utilised as a research framework.

Characteristics of the technological factor that were discovered to be used the most were complexity, divisibility, social approval, observability, relative advantage, cost, trialability, communicability, compatibility, and profitability (Tornatzky & Klein, 1982). Certain characteristics were shown to be consistently related to adoption of technology (Bhattacharya & Wamba, 2015). These include the relative advantage or perceived benefits of the technology and the compatibility and complexity of the technology relative to an organisation’s existing IT infrastructure.

The initial challenge usually posed at the beginning of an AI technology adoption journey is the cost of implementation of the new technology and the hardware and software cost. The cost saving benefit of implementing a new technology links to the perceived benefits of the technology adoption (Mittal et al., 2017). Past studies have not adequately considered factors such as data availability which is an important factor for AI adoption.

Factors identified from an organisational context are top management support, firm size, IT resource capability and presence of product champions (Baker, 2011). Various studies argue that top management support is positively related to technology adoption and diffusion of innovation theory (Rogers, 1995). Management teams that create an environment conducive to technological change have smoother adoption processes (Chen, Li, & Chen, 2021). Other favourable conditions for adoption were the availability of IT resource capability across the organisation. Resource capability was discovered to be significant in implementation and adoption decisions for RFID in the retail sector and EDI and e-commerce studies (Bhattacharya & Wamba, 2015).

Competitive analysis was found to be a factor that positively influenced adoption in studies of cloud computing, mobile banking adoption and information technology adoption in the manufacturing industry (Duh & Fabiao, 2018; Gutierrez, Boukrami, & Lumsden, 2015).

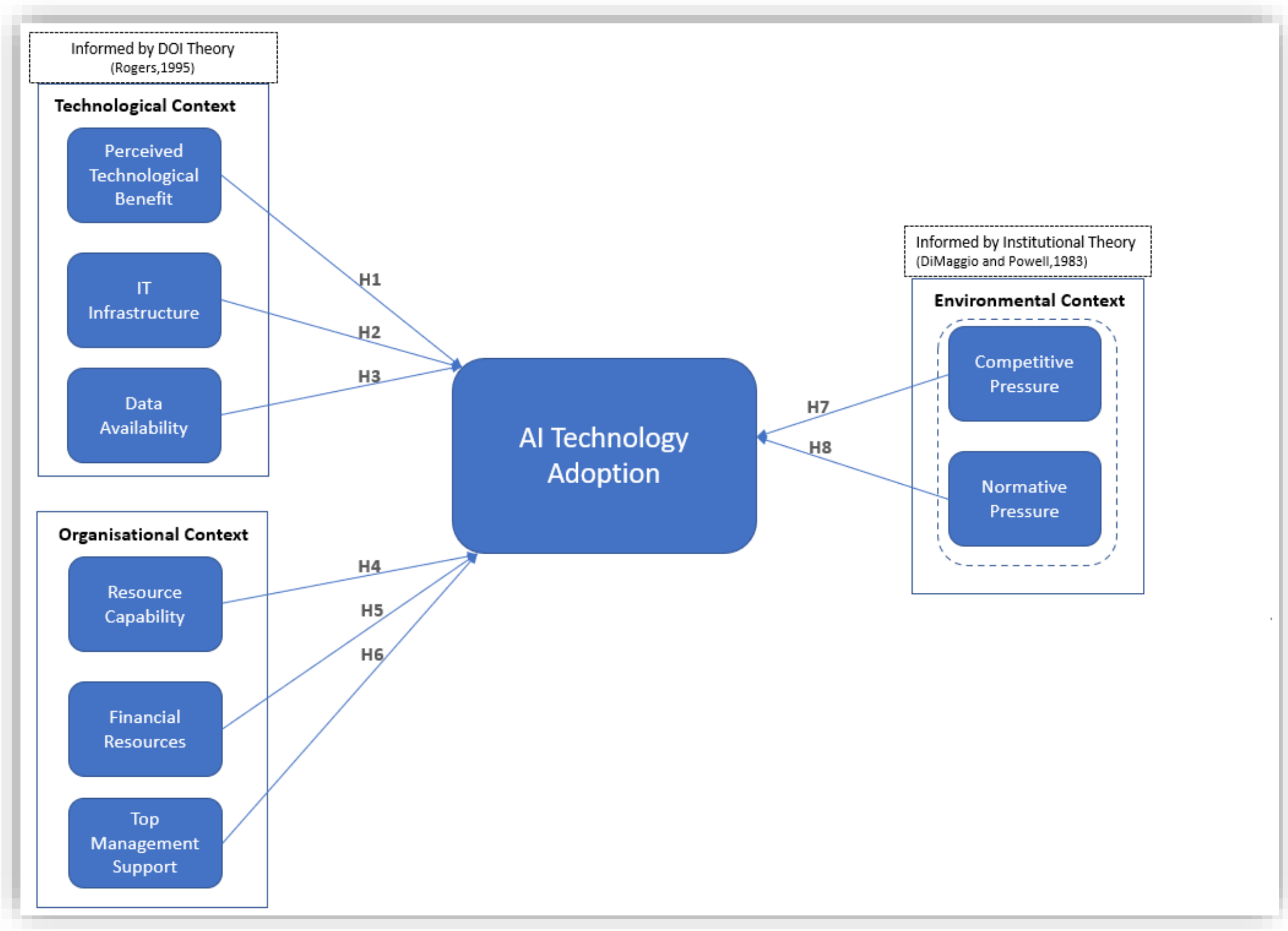

Figure 3. 2: Research Model displaying the factors that influence South African organisations adoption decision

3.2.2 Technological Context

Perceived Technological Benefit

Perceive technological benefit is recognised as the projected advantages that the adoption of artificial intelligence will provide to the organisation (Gutierrez, Boukrami, & Lumsden, 2015). As senior stakeholders and partners start utilising the benefits of AI adoption in the organisation, other areas of the business will be influenced as results and benefits of innovation will flow through (Suer, 2019). Some of the perceived technological benefits are highlighted below.

- **Automated data utilisation aids in reducing fraud in organisations:**

AI algorithms are designed to learn from patterns and experiences. The more data provided to an AI, the better the AI becomes (Donepudi, 2017). AI technology provides organisations with the ability to identify data trends and easily build visual models to identify irregular data patterns or behaviour (KPMG, 2020).

With organisations having the ability to easily identify irregular or abnormal customer behaviour at the touch of their fingertips, fraudulent activity will be reduced (Columbus, 2018).

- **<u>Increased Customer Advantage:</u>**

The definition of customisation is redefined by AI technology. AI technology automates the process of pulling together customer data and makes the product offering personalised to the customer by collating all the activity or history of that customer within the organisation (BCX, 2017; Trehan, 2020). The predictive mechanisms are made more accurate by using a combination of structured and unstructured data about the customer, making requesting a new product for a customer easier and more convenient (Trehan, 2020).

The entire consumer footprint can be understood through AI technology, which is an enormous advantage for South African organisations (Matallanas, 2022; Moyo, 2021). The holistic view allows financial institutions to understand the fiscal status of a customer across various accounts in an instant (Trehan, 2020). Similarly, other industries such as retail and manufacturing are benefiting from having their customer data available to them for analysis, other than improving cost and savings in organisations, company forecasting has become more efficient as managers can estimate stock of materials or products certifying that the correct amount of stock is available, avoiding excess or shortage of stock (Matallanas, 2022)

- **<u>Drive Innovation:</u>**

For many years innovation has been a buzz word in organisations. Innovation is known as the formation or discovery of new ideas, services, products, or processes (Suer, 2019). Innovations have become increasingly significant in the competitive age that we in and is known as a key business enabler for organisations looking to gain sustainable competitive advantage and increased value. Innovation can come in the form of new products, technology innovations or improvements. Improvements are new solutions that are intended to solve existing business problems and value propositions while new innovations produce a novel path, value propositions and are more radical (Breakstone, 2019). Organisations that have shown great innovation capabilities respond better to business change. Innovation within South African organisations will increase as resources will have more time to focus on solving complex tasks. This will result in efficient processes and products being produced (Access Partnership, 2018). The relationship between perceived benefits and adoption of AI has been supported in previous research in the banking industry by Mariemuthu (2019). This leads to the following hypotheses:

H1. *The greater the perceived benefits of AI technology, the greater the likelihood of adoption.*

- **<u>Information Technology (IT) Infrastructure:</u>**

IT infrastructure plays a crucial role in an organisations decision to adopt new innovations or technology.

Computer hardware, software, database servers, shared drives and virtual machines amongst others are examples of IT infrastructure (IBM, 2020). Organisations will need to fully migrate to the cloud to enjoy the full benefits of AI. The traditional infrastructure mentioned above will not perform well on big-data types of technological tools (KPMG, 2020). Amazon web services (AWS) is one of the companies that have AI infrastructure in place for organisations to leverage off. Most of the AI infrastructure products on offer by Amazon grant organisations trial periods creating flexibility for organisations to determine if they want to take up the commitment of updating their infrastructure to accommodate AI technology (Amazon Web Services, 2022; Storrar, 2021).

Availability of infrastructure refers to the period of time that servers, operational systems, or sites are up and running and generating business value (IBM, 2020). The availability of the latest infrastructure technology within the organisation will positively influence the adoption decision within the firm as this will lead to reduced costs and timelines associated with the innovation (Accenture, 2019). The relationship between artificial intelligence technology adoption and IT infrastructure is supported in Mariemuthu (2019). This leads to the following hypotheses:

H2. *The greater the availability of advanced information technology infrastructure for AI technology, the greater the likelihood of adoption.*

Data Availability:

AI algorithms are data dependent and require good quality data to perform optimally (Accenture, 2017). Good quality data can be defined as data that is complete, accurate and accessible (Deloitte, 2021). Different organisations will vary on the definition of good quality data. For this context, good data quality will be known as how well does a specific set of data service the current business requirement. For organisations to attain good accuracy and prediction in models, large amounts of data from different sources are required (Hassani, Huang, Silva, & Ghodsi, 2020). Some sources of data include 3rd party data, data produced within the organisation from various business units or the media.

The availability of data refers to both accessibility and continuity of information. Data that is difficult to access timeously can hinder business processes and slow down service turnaround times, losing the organisation time and money (Ammanath, Jarvis, & Hupfer, 2020).

Since most managers are unaware of the outcomes that their data can provide, data can remain underutilised. Managers should become data champions and focus on security, governance, and regulation for an end-to-end data supply chain (Accenture, 2019). This leads to the following hypotheses:

H3. *The greater the availability of good quality data for AI technology, the greater the likelihood of adoption.*

3.2.3 Organisational Context

Top Management Support:

In addition to resource capability and financial resources, top management support is also an important element in the adoption decision (Accenture, 2019; Liang, Saraf, Hu, & Xue, 2007). Baker (2011), states that top management teams should aim to create collaborative environments that promote innovation of new technologies. The organisations vision and strategy should be shared with all employees and the relevant support to embrace the adoption should be provided (Gartner, 2019). Implementation of new technology requires many changes within the organisation. AI adoption is an enormous change for most organisations. A great deal of preparation goes in from all aspects of the business to successfully incorporate AI technology. Top management need to drive this change and make visible the benefits of the change to other business partners and employees (Gartner, 2019; Global, 2018). The chief technology officer of Bank of America states that their approach to AI adoption is to integrate this new technology into their strategy and culture. Their key to drive AI in their organisation is to build trust, responsibility, and customer centricity amongst employees (Mckendrick, 2021). The relationship between top management support and IT adoption was supported by past studies for cloud computing (Gutierrez, Boukrami, & Lumsden, 2015), RFID (Bhattacharya & Wamba, 2015), and mobile banking adoption (Duh & Fabiao, 2018). This leads to the following hypotheses:

H4. *The greater the support from Top Management, the greater the likelihood of adoption.*

Financial Resources:

An organisations financial state and affordability of infrastructure and resources required for the adoption play a key role in the final decision (Accenture, 2017). For example, the cost of migrating an organisations database to the cloud to support their AI technology performance demands high cost (Accenture, 2017). The maintenance cost after implementation is also a factor that hinders adoption of new technology (AnalyticsWeek, 2020). Organisations that have been preparing and setting aside more money towards their technology investments will be more likely to take the leap and adopt (Access Partnership, 2018).

This leads to the following hypotheses:

H5. *The greater the financial resources required for AI technology, the lesser the likelihood of adoption.*

Resource Capability:

Lack of resource capability will impact the adoption decision negatively. Without the right skillset required for the adoption, the implementation of the new technology could be delayed. AI technology is an evolving technology with a unique skillset (Van Buren et al., 2020). AI algorithms can be difficult to create depending on the complexity of the problem being solved. Organisations need to consider training current talent as one of their initial steps of adoption and refine skillsets as the technology improves (Van Buren et al., 2020). Bhattacharya & Wamba (2015) studied RFID adoption and found that IT skills or resource capability is an important factor in technology adoption. This leads to the following hypotheses:

H6. *The greater the AI technology resource capability within South African organisations, the greater the likelihood of adoption.*

3.2.4 Environmental Context

Competitive Pressure:

Mimetic pressure occurs when organisational players look to other firms for examples of success. It is an act of voluntarily copying other established organisations examples and practices that made them successful (Shi, Shambare, & Wang, 2008; BCX, 2017). The benefit established from mimicking other firms can help save on experimentation and search costs, indirectly avoiding risk. Organisations are more likely to adopt AI technology if they recognise AI technology to be a valid measure of success from other trusted organisations (Chen, Li, & Chen, 2021). The type of mimetic pressure that will be focused on is **competitive pressure**.

Competitive pressure occurs from the fear of losing competitive advantage. An organisation's decision to adopt is influenced by competitive advantage (Aspen Publishers Inc, 2021). Wang & Cheung (2004), established in their research that competitive pressure positively influenced adoption behaviour. Organisations are constantly competing to provide the best products and services to their customers (Lui & Lamb, 2018). By adopting AI technology, organisations can gain the competitive edge against their competitors. The relationship between competitive pressure has been consistently supported in prior research for technology adoption across industries, for e.g., Oliveira and Martins (2010) used competitive pressure in their E-Business adoption study, Ghobakhloo, et al (2011) and Chen, et al (2021) identified competitive pressure as a factor in their IT adoption studies for technology adoption in manufacturing SME's and AI in the telecom industry, respectively. This leads to the following hypotheses:

H7. *Organisations experiencing high levels of competitive pressure are more likely to adopt AI technology.*

Normative Pressure:

Normative pressure occurs when institutions or organisational players look at other firms' adoption of innovation and is influenced to behave in an equivalent way (Teo, Wei, & Benbasat, 2003). Norms can be shared using social networks amongst representatives where there is an increase in consensus thus increasing the power of the norms and the influence on organisational behavior (Teo, Wei, & Benbasat, 2003). The benefit established from mimicking other firms can help save on experimentation and search costs, indirectly avoiding risk. Organisations are more likely to adopt AI technology if they recognise AI technology to be a valid measure of success from other trusted organisations (Chen, Li, & Chen, 2021). Teo, Wei & Benbasat (2003) found normative pressure important in their study to understand interorganisational system adoption.

This leads to the following hypotheses:

H8. *Organisations experiencing high levels of normative pressure are more likely to adopt AI technology*.

3.3 Conclusion: Chapter 3

This chapter presented an overview of the Technology Organisation Environment (TOE) framework and developed the eight hypotheses summarised below.

Number	**Hypothesis**
H1	The greater the perceived benefits of AI technology, the greater the likelihood of adoption.
H2	The greater the availability of advanced information technology infrastructure for AI technology, the greater the likelihood of adoption.
H3	The greater the availability of good quality data for AI technology, the greater the likelihood of adoption.
H4	The greater the support from Top Management, the greater the likelihood of adoption.
H5	The greater the financial resources required for AI technology, the lesser the likelihood of adoption.
H6	The greater the AI technology resource capability within South African organisations, the greater the likelihood of adoption.
H7	Organisations experiencing high levels of competitive pressure are more likely to adopt AI technology.
H8	Organisations experiencing high levels of normative pressure are more likely to adopt AI technology

Table 3. 2: Overview of Hypotheses

Chapter 4 will describe the research methodology and the research methods used for the study.

Chapter 4: Research Methodology

The research methodology chapter discusses the research paradigm, approach, data collection methods and the outcome of the pre and pilot test.

4.1 Research Paradigm and Approach

Epistemology refers to the study of knowledge. Epistemology supports researchers with their approach and their assumptions by providing the ideal manner to study a phenomenon of interest (Bhattacherjee, 2012).

Interpretive research paradigms utilize an inductive approach which begins with data and then develops a theory from the observed data about the phenomenon of interest. The approach is deemed to be subjective and is governed by the scholar's understanding of the subject (Bhattacherjee, 2012; Bryman & Bell, 2015). Interpretivism does not support the idea of an unbiased social or tangible world that exists separately from people (Bhattacherjee, 2012). On the other hand, the positivist research paradigm is popularly recognized for testing theories or hypotheses and adopts a deductive approach. This means that the approach begins with the theory and then testing of the applicable theory with the data that was gathered for the study (Bhattacherjee, 2012; Bryman & Bell, 2015).

The study is informed by the positivist approach as it intends to examine the associations between the dependent and independent variables. Positivist research is eminent for scientific measures and robust propositions and applies empirical testing to analyse measures (Oates, 2006). The theories studied can be accepted or rejected and the outcome of proving or disproving a theory forms the foundation for scholars to disclose associations to envisage or support behaviours or patterns (Oates, 2006; Bhattacherjee, 2012). Positivism uses instruments that are valid and controlled to investigate the occurrence of relationships amongst proven variables. Scientific measures of the established variables are employed to test the theory and conclusions are derived and generalised from the sample to the population (Bhattacherjee, 2012).

4.2 Research Design and Methodology

Since the research study will focus on measuring the TOE factors and testing of hypotheses it was decided that the quantitative method will be suitable for this study. Quantitative research is the practice of collecting and studying statistical data (Bhattacherjee, 2012). A cross-sectional research design was chosen for the study with a structured instrument (Bryman & Bell, 2015). This was based on the factors identified and what the study is aiming to measure in terms of an organisations tendency to adopt a technology.

Research design refers to the overall strategy chosen. The research design incorporates various elements of the research study in a consistent and logical manner. It serves as the blueprint for the gathering, examining and measurement of data and successfully ensures that the research question is being addressed (Bhattacherjee, 2012). Exploratory, experimental, relational, descriptive, and explanatory are all classified as research designs. Exploratory research is predominantly used when the problem being investigated is at the initial stage (Bhattacherjee, 2012). Experimental research stringently follows a scientific design approach and is focused on examining the cause and effect of relationships (Bhattacherjee, 2012; Bryman & Bell, 2015). As the name suggests, explanatory research concentrates on explaining the various parts of the study and aims to answer why or how the research problem happens (Oates, 2006). Descriptive research concentrates on producing careful observations and comprehensive documentation on the phenomenon being studied (Bhattacherjee, 2012). Relational research design was chosen for this study. The relational research design studies the association amongst two of more variables (Bhattacherjee, 2012). The variables being evaluated usually already exist in the population or study. The analysis of the TOE factors influencing AI adoption by South African organisations will be answered through a quantitative study following a relational research design.

To demonstrate the behaviour of South African organisations, large groups of participants would be required for data collection. Since this will be unfeasible because of resource and time limits, a subset of the population will be used to collect data (Bryman & Bell, 2015). Survey research was the chosen method for this study as it allows the researcher flexibility to generalize results from the sample population to the wider population with the aim of facilitating statistical conclusions concerning the behaviour, mindset, or attributes of the population (Bryman & Bell, 2015). Survey research entails the usage of structured questionnaires and interviews to gather data from the participants that defines the mindset, attributes, or behaviour of the population (Bhattacherjee, 2012; Bryman & Bell, 2015). Researchers should take note of the fact that surveys will not be able to illustrate biasness from the respondents or show causation (Bryman & Bell, 2015). It was revealed from past studies that drew on the TOE framework that the survey method used in conjunction with the relational research design is a suitable approach.

4.3 Data Collection Methods

4.3.1 Sampling, Respondents and Data Collection

Unit of analysis is described as the prime object being investigated in a research report (Bhattacherjee, 2012). The aim of this study is to evaluate the adoption behaviour of selected South African organisations. The unit of analysis chosen for the study are business areas in South African organisations. Sampling is the process of statistically selecting a sample also known as a subset of the population of interest to gather observations and statistical assumptions about the selected population (Bhattacherjee, 2012). A sampling frame represents a segment of the target population that is accessible (Bhattacherjee, 2012; Oates, 2006). The Johannesburg Stock Exchange (JSE) website provides a readily available sampling frame. The list of JSE listed companies will be reviewed to construct a suitable sample that will represent the financial, retail and manufacturing industries. It was deemed appropriate for constructing a purposive non-probability sample. Non-probability sampling is a sampling technique that is founded on the purpose of the study and the characteristics that a specific population represents (Bryman & Bell, 2015).

The sampling frame was created using the list of companies registered on the Johannesburg Stock Exchange (JSE). A list of both locally controlled and foreign controlled organisations was considered. The list contained 262 organisations (Johannesburg Stock Exchange, 2022). Out of the 262 organisations listed, 10 were categorized as part of the health sector and were excluded from the sampling frame. The JSE website contains a high-level breakdown of executive members of the organisations listed. Further research using online tools assisted in gathering a detailed list of IT executives including contact details.

The survey was directed at key informants such as senior IT leaders who are the decision makers of their business areas in their organisations. IT leaders or decision makers refer to those individuals who are mandated to authorise new technologies such as AI in their organisation. IT senior managers, IT business heads, chief information technology and data officers, and information technology executives were classified as the decision makers (Gartner, 2019; Mariemuthu, 2019). It is common practice across TOE adoption studies to utilise IT leaders or decision makers. Studies include Chen, Li, & Chen (2021) on AI success factors, Gutierrez, Boukrami, & Lumsden (2015) on cloud computing and Duh & Fabiao (2018) on mobile banking adoption. IT leaders chosen for past studies were considered as they had a good understanding of current trends and their current organisational position.

The names of the 252 listed South African organisations were used in a google search to yield the results of the various industries chief information officers (CIO). A further search was conducted using the names of the CIOs to search for other leaders in their organisations such as IT managers, data officers, technology officers etc. Invitations to participate were sent via email to the identified participants prior to the survey being sent to increase the response rate.

4.3.2 Instrument development and Operationalization

A cross-sectional survey instrument was chosen for this study. The dependent and independent variables were measured using multi-item scales included in an online web survey. Online web surveys are classified as an independent researcher method (Bryman & Bell, 2015). Some benefits include secure storage of participant data, cost effective administration, customization of the survey and easy access link provided to participants (Bhattacherjee, 2012).

Structured survey was used as the instrument of choice to investigate the factors that influence AI adoption in South African organisations. The process of converting theoretical concepts into an indicator that can be measured and defined is known as operationalization (Bhattacherjee, 2012). To form items that can be measured, IT literature was consulted and assessed. Seven-point Likert scales (1=strongly disagree and 7=strongly agree) were used to measure the independent variables. Likert scales are commonly used in IS studies to measure ordinal data. It provides 7 possible options to participants inclusive of a neutral option, this allows participants to easily answer questions (Bhattacherjee, 2012; Bryman & Bell, 2015). A notable benefit of Likert scales is that results are computable and easy to assess. Prior literature was used as the base for operationalization of scales to justify the survey's content validity.

In this study, the dependent variable known as adoption was measured with the following: current level of adoption, investment in AI technology and strategy to guide AI adoption (Radhakrishnan & Chattopadhyay, 2020). The technology, organisation and environment factors form the independent variables. Table 4.1 below describes the independent variables in the study and how each item was constructed for the survey.

Taken together the survey included the following sections:

- Demographic data
- AI technology adoption in the organisations
- Technology context
- Organisation context
- Environment context

Independent Variable	Definition	Survey Items	Sources
Perceived technology benefit	The Perceived technology benefit is the benefit that organisations will realise with the adoption of AI technology. Objects such as increased flexibility, reduced cost and increased customer advantage will be used to measure the perceived technological benefit of AI technology (Suer, 2019).	Why is AI adoption significant to your business area?	(Mariemuthu, 2019; Suer, 2019)
		PTB.1 AI can reduce operational costs in my business unit	
		PTB.2 AI is important to improve process efficiency in my business unit	
		PTB.3 AI is vital to reach new customers for my business unit	
Information Technology (IT) infrastructure	IT infrastructure represents the technology that provides the groundwork for AI capabilities to operate on. Databases, servers, computer hardware and software are examples of IT infrastructure. To measure this element, objects such as compatibility and availability of IT infrastructure will be measured (IBM, 2020).	ITF.1 AI will be compatible with supplier or customer software	(Oliveira & Martins, 2010; IBM, 2020)
		ITF.2 My business area infrastructure can support AI technology	
		ITF.3 The development of AI technology is compatible with my organisation's legacy systems	
Data availability	Data availability refers to the dependability and timeliness of access to data (Ammanath, Jarvis, & Hupfer, Thriving in the era of pervasive AI, 2020).	DA.1 My business area has access to data required for AI	(Chen, Li, & Chen, 2021; (Ammanath, Jarvis, & Hupfer, Thriving in the era of pervasive AI, 2020).)
		DA.2 Data supplied from my business unit is of good quality (complete, accurate)	
		DA.3 My organisation has a data repository to store and process large amounts of data at an acceptable speed	

Resource capability	Resource capability refers to the skills available within the organisation and other critical skills required to implement AI technology. This element will be measured by considering the following measures: the current AI skills available in the organisation, the type of AI technology skills required to close the skills gap in the organisation and if newly skilled colleagues will be enthusiastic to share knowledge with others in the organisation (Duh & Fabiao, 2018).	RC.1 Regular training occurs in my business area to ensure employees are acquainted with AI technologies RC.2 My business area encompasses a high level of AI associated knowledge RC.3 The rate of hire for highly skilled AI employees is regular in my business area	(Duh & Fabiao, 2018)
Financial resources	Financial resources refer to the costs associated with the adoption of artificial intelligence technology. Costs for AI technology consist of setup costs, maintenance costs and training costs. The three cost factors mentioned will be used to measure this element (Accenture, 2017).	FR.1 High setup costs are associated with AI technologies FR. 2 High maintenance costs are associated with AI technologies FR. 3 AI adoption comes with resource training costs	(Bhattacharya & Wamba, 2015; Accenture, 2017; Duh & Fabiao, 2018)
Top management support	Top management support is associated with how senior management in an organisation support and influence the adoption of AI technology through communicating the strategy and vision to employees in the organisation and fostering collaboration and innovation in the workplace. Measures such as Top management influence, strategic alignment, vision and competitive influences and funding will be considered (Gutierrez, Boukrami, & Lumsden, 2015).	TMS.1 Investment in AI technology is supported by top management in my business area TMS.2 AI technology is considered by top management in my business area to offer a competitive advantage TMS.3 AI is deemed strategically important by top management in my business area	(Gutierrez, Boukrami, & Lumsden, 2015)

Normative Pressure	Normative pressure refers to organisational players being influenced by related networks to adopt technology practices from organisations that are deemed to be successful. To measure this element, objects such as success measures of other similar organisations will be investigated, the rate of their success before and after adoption and their perceived influence amongst their customers after adoption of AI Technology (Teo, Wei, & Benbasat, 2003).	N.1 Our customers have adopted AI extensively N.2 Our suppliers have adopted AI extensively N.3 AI adoption is a norm for our industry N.4 Trade and industry bodies relevant to our organisation promote the use of AI	(Teo, Wei, & Benbasat, 2003; Krell, Matook, & Rohde, 2016)
Competitive pressure	Competitive pressure occurs when organisations want to hold on to their competitive edge to stay ahead of other industry players. Objects that will be taken into consideration to measure this element are the level of competitive pressure faced by an organisation or department and the implications that the organisation will face if AI technology is not adopted by the organisation (Ghobakhloo, Benitez-Amado, & Aranda, 2011).	C.1 A high percentage of my organisations direct competitors use AI technology C.2 Our direct competitors that have adopted AI are seen favourably by their customers in the market C.3 Our direct competitors that have adopted AI are seen favourably by their suppliers in the market C.4 Our direct competitors that have adopted AI are seeing great benefits	(Krell, Matook, & Rohde, 2016)
Current state of Artificial Intelligence adoption	The adoption of AI technology by South African organisations. AI technology adoption is the dependent variable in this study	A.1 My business area is satisfied with our current level of adoption A.2 My business area invests adequately in artificial intelligence technology A.2 My business area has a strategy in place to guide AI adoption • Machine — Yes, already adopted	(Radhakrishnan & Chattopadhyay, 2020)

		Learning • Natural language processing • Neural networks • Robotics process automation • Chat bots | Virtual assistants • Image recognition • Speech recognition	Not yet adopted, but we have plans to adopt within the next 1 -3 years Not yet adopted, but we have plans to adopt within the next 3 -5 years No plans to adopt Unsure	

Table 4. 1: Breakdown of survey item

4.3.3 Pre and Pilot testing

4.3.3.1 Pre – test

The pre-test served two purposes. Firstly, it provided additional evidence to support an answer to Research question one, namely the identification of a relevant basket of AI technologies. Secondly the pre-testing was conducted for the survey instrument to improve the content and face validity. The survey would provide the data needed to test the hypotheses pertaining to Research question two. Pretesting of instruments are conducted to increase precision of the survey and to eliminate vagueness and biasness in the question wording before distributing the final survey to the selected sample population (Bhattacherjee, 2012). IT professionals at various South African organisations were approached to review the survey content. The IT professionals that were interviewed were senior IT finance partner, Lead solution architect, Metallurgist and Chief Operating Officer of a Trade finance company. Research question one was answered through questions posed on the pre-test survey. The types of AI technology used in organisations were confirmed through the pre-test survey. Based on the feedback received, the following adjustments were made to the survey as shown in table 4.2.

Section/ Question No.	Item – As is	Item – To be	Comment
A – Demographic Data	Please specify your organisational cluster • Technology • Retail Industry • Basic Materials • Financial Institution • Industrial • Telecommunication • Oil & Gas • Other	Please specify your organisational cluster • Technology • Retail Industry • Basic Materials • Financial Institution • Industrial • Telecommunication • Oil & Gas • Mining • Other	Question 4 under section A to include mining as an option as the maturity levels in mining is not comparable to manufacturing or other areas which comprise “industrial”
Section A	Please answer the following question about yourself and your business area	Please answer the following questions about yourself and your business area	Grammar corrected
Question 2	Please state how long you have been in your current role?	Please state how long you have been in your current job role?	Question rephrased
Question 3	Please state the duration that you have been with your current organisation?	Please state the duration that you have been with your current organisation?	Switched with question 2
Question 4	Please specify your organisational cluster	Please specify your organisation’s industry sector	Grammar corrected
Question 6	Please specify which of the artificial intelligence	Please specify which of the following artificial	Question rephrased

	technologies have been implemented in your business area	intelligence technologies have been implemented in your business area	
Question 6	Options: Yes/No	Options: • Yes, already adopted • Not yet adopted, but we have plans to adopt within the next 1-3 years • Not yet adopted, but we have plans to adopt within the next 3-5 years • No plans to adopt • Unsure	Question 6 options expanded
Question 6	Expert Systems	Neural Networks	AI option updated to reflect finding from SLR
Question 7	Please state year of adoption for the technologies below and how the technology was implemented in your business area	Please state year the technology was first adopted	Question rephrased
Question 7	Adoption – Year 1	Year Adopted (If applicable)	Option rephrased
Question 9	My business area is satisfied with the current level of adoption	My business area is satisfied with our current level of adoption of AI technologies	Question rephrased

Table 4. 2: Survey updates post pre-test

Based on the results of the pretest, the survey was found to be effective and valid for collecting data on the factors that influence AI adoption in organisations. The pretest confirmed that the list of AI technologies relevant for South African organisations as shown in the table 4.3 below.

Type of AI Technology	**Definition**
Machine learning	Machine learning focuses on providing self-learning capabilities to computers and systems to adapt and improve through experiences without the need for explicit programming (Donepudi, 2017; KPMG, 2020).
Natural Language Processing (NLP)	The objective of natural language processing is to support computers to comprehend, analyze and generate human language in a manner that is both meaningful and beneficial (Grguric, Vlacic, & Drvenkar, 2020).
Robotics Process Automation (RPA)	RPA is software that is governed by rules to mimic

	human actions (Ammanath, 2022).
Chatbots/ Virtual Assistants	Chatbots are system programs used to simulate human conversation and interact with humans in a conversational manner (Benbya, Pachidi, & Jarvenpaa, 2021).
Neural networks	Neural networks were conceptualized from the structure and formation of the human brain. It is made up of units that are arranged in layers to process and learn from input data (Hradecky, Kennell, Cai, & Davidson, August 2022).
Image recognition	Image recognition uses algorithms to identify and classify objects or patterns (Kabalisa & Altmann, 2021).
Speech recognition	Speech recognition converts human speech into text (Alhawti, 2015).

Table 4. 3: Suite of AI technologies identified post SLR and pre-test

Three out of five participants claimed that although AI adoption is visible in their organisations, planned usage of the technology is in infancy stage so the benefits of using AI have not been realized yet. The pre-test results summary is included in Appendix A.

4.3.3.2 Pilot Test

After the pre-test a pilot test was performed. The survey was updated with the possible suggestions received. Pilot testing is a small study conducted prior to the official distribution of the instrument to participants (Bhattacherjee, 2012). The researcher made changes to the instrument based on the feedback received from the participants. The purpose of the pilot test was to confirm face validity as well as to ensure that the technology, organisation, and environment framework are reliably measured. The following questions were asked on completion of the pilot test:

- Are the questions simple to understand? If not, please specify the questions that need improvement.
- Is the survey an appropriate length or is it too long? Please state the time taken to finish the survey.
- In your opinion, were there any questions that were applicable to the study that was left out?

The pilot test was conducted with a subset of five participants of the selected sample population. The responses were analysed to identify inconsistencies in the responses to confirm if the participants had the same understanding of the items in the survey. The results from the pilot test would not be included in the final study and would serve to improve the main survey.

The participants were comfortable with the length of the survey. The structure and wording of the survey remained the same with no additional changes suggested by the participants. The summary of the pilot test results is included in Appendix B.

4.3.4 Survey administration

Once the pilot test was complete, the final survey was circulated to the selected sampled population. Communication (with an official cover letter) was sent using the official Witwatersrand email address to IT leaders to welcome them and encourage their participation in the survey. Accessibility of the survey was through an online survey portal using a URL link. The web survey is considered appropriate as IT leaders are generally comfortable with technology and connected. The speed, anonymity, and response also it is an attractive tool for the study (Bhattacherjee, 2012). A possible drawback of the web survey is that the link may be deemed to be suspicious and denied by participants for security purposes. 252 participants were identified as part of the sample population, emails were sent to all 252.

The survey was open for approximately 1 month. Follow – up emails were sent after every three days, and frequency of responses were monitored. Research conducted by Sheehan and Hoy (1997) suggest that reminder emails potentially increase the rate of response by approximately 25 percent. After the final reminders were sent, a total of 57 responses had been received for the purposes of analysis.

4.4 Data Analysis Methods

4.4.1 Reliability and validity

Data that was collected for the survey was evaluated to detect the occurrence of missing data or errors in the data from participants (Bhattacherjee, 2012; Crestwell, 2012). SPSS software was used to analyse the data. The validity of the scales employed were tested. Construct validity is the degree to which a particular measure performs in a manner that is consistent with the hypotheses that it is the expected measure (Bhattacherjee, 2012; Crestwell, 2012). Past research was applied as a base for content validity while a pilot test was conducted to ensure face validity (Bhattacherjee, 2012; Mariemuthu, 2019). Construct validity was further assessed by convergent and discriminant validity tests (Crestwell, 2012). Convergent validity tests indicate how strongly related a measure is to other measures of the same construct. Discriminant validity tests are used to confirm measures do not correlate too strongly with those of unrelated constructs (Bryman & Bell, 2015; Crestwell, 2012). To test convergent and discriminant validity, principal component analysis was employed.

Principle components analysis is a technique used to reduce a substantial number of variables to a more manageable amount, and through examination of factor loadings can be used to confirm convergent and discriminant validity. Convergent validity is achieved once measurement items load highly on their expected construct. Discriminant validity is accomplished when measurement items have minimal factor loadings on variables they are not intended to measure (Crestwell, 2012; Mariemuthu, 2019).

Measurement scales were also evaluated to determine reliability. Internal consistency reliability refers to the degree of consistency observed among different items that measure the same construct (Crestwell, 2012; Bhattacherjee, 2012). The degree to which respondents ranked items on the survey determined internal consistency, bearing in mind that multi-item constructs were given to respondents. Cronbach's alpha is deemed appropriate by Bryman & Bell (2015) to measure internal consistency reliability. A co-efficient of 0.93 is considered high and 0.72 is deemed satisfactory. Once convergent and discriminant validity and internal consistency reliability were assessed, hypothesis testing as the basis for answering Research question two could then proceed.

4.4.2 Hypothesis Testing

The hypotheses highlighted for the conceptual model were used to test Research question two. Correlation analysis was used first to examine the relationship between the dependent AI adoption variable and the various independent variables, thereafter multiple regression and finally step-wise regression. Hypothesis tests are usually produced from a sample and there is a likelihood of errors arising. Rejecting a true null hypothesis result in a Type I error. Failing to reject a false null hypothesis is known as Type II error (Oates, 2006). The probability of creating a Type I error is dependent on the significance level α and $p \leq 0.05$ depicts the intended relationship between p-value and α (Khan Academy, 2022). The study will use the p-value methodology to determine statistical importance. The null hypothesis will be rejected if the $\text{p-value} < 0.05$ (Bhattacherjee, 2012; Mariemuthu, 2019). An F-test will be used to establish if a meaningful relationship occurs between the independent and dependent variables. An F-test signifies if the regression model being utilized offers a better fit for the data compared to a model with no independent variables (Khan Academy, 2022). When a relationship of significance exists amongst the dependent and independent variable then the hypothesis is supported (Bryman & Bell, 2015; Crestwell, 2012).

The hypothesis testing will thus determine the significance of and extent to which the selected technological, organisational, and environmental factors influence AI adoption, and thus provide an answer to Research question two.

4.5 Ethical Considerations

The study conformed to strict observance of the five ethical principles for confidentiality, anonymity, disclosure, harmlessness, reporting and investigation (Oates, 2006). A cover letter accompanied the survey to advise possible participants of the goals of the study. The participants were advised that their involvement in the study is completely optional, and no loss or penalties of any kind will be experienced if they choose not to participate. Moreover, the data that was provided by the participants can be withdrawn at any time without consequences and this was also noted in the cover letter (Oates, 2006).

Anonymity of responses was also highlighted in the letter and participants were informed that their answers will not be linked back to their areas of business, this is especially important to the selected set of participants. Due to the nature of the sample population, no customer information relating to organisations was requested to ensure that client data confidentiality is protected and will not be at risk of being exposed (Oates, 2006; Rosenthal, 1994). Acquired data was stored safely and confidentially and protected. The data will not be distributed to third party companies or other organisations' business units that are surveyed. The responses from participants were retrieved only by the researcher and supervisor and were not available to third parties. Lastly, data was collated and aggregated and was not analyzed on individual replies (Rosenthal, 1994).

The research study was presented to the relevant University ethics committee for clearance. The School of Business Science ethics committee approved the study (Protocol number CBUSE2062). Please refer to Appendix D to view the ethics clearance certificate.

4.6 Limitations and threats to internal and external validity

The study conducted was subject to certain conditions or limitations. The study was cross sectional in nature, the noted limitation is that the study will not provide an understanding for how the relationships of the variables will shift over time. Future researchers can explore a longitudinal study. In this study, underlying assumptions about causality can be developed only with reference to academic theory and literature.

The concentration of the research is on AI adoption decisions by South African organisations and not on AI technology implementation experiences of organisations, or the extent of actual benefit realisation.

External validity states how results of a specific study can be generalised to other applicable studies (Bhattacherjee, 2012). The non-probability sampling approach that was used in the study poses a risk to external validity as the outcomes of the research may not be generalizable across other organisations not studied. Additionally, results may not be generalizable to other countries due to the unique developmental and economic context influencing technology innovation of South African organisations.

In addition, even though the surveys were targeted at IT leaders of business areas in South African organisations, there is no guarantee that the surveys will be completed by the IT leaders. Respondent bias is potentially a possibility due to the data being self-reported, an example would be social desirability bias such as where respondents may be prone to exaggerate their extent of AI adoption.

Conclusion: Chapter 4

Chapter 4 presented the research method, sampling frame, design, and limitations of the study. The chapter also developed and operationalized the instrument. Pre and pilot testing was used to confirm reliability and validity of the survey. Methods for data analysis were also reported. Ethical considerations for the research were also discussed. Chapter 5 will outline the research findings.

Chapter 5: Research Findings

Chapter five presents the results of analysis on the data that was collected through the survey for the purpose of addressing the study's second research question. First data screening is discussed and thereafter the profile of survey participants. The analysis, interpretations, and findings are then presented in relation to the current state of AI adoption, followed by reliability and validity testing and tests of hypotheses to identify the factors most important to AI adoption.

5.1 Data Screening

The data collected underwent a rigorous data screening process to ensure reliability and validity of the data. This process consisted of data cleaning, reverse scoring, and outlier detection. The total number of participants identified was 252. Surveys were distributed to all 252 participants. Eight respondents chose not to participate and informed the researcher via email. After 4 weeks of data collection, a total number of 57 responses were received. The responses represented 22.6% of the sample population. Other studies using the TOE framework namely Bhattacharya and Wamba (2015) and Ghobakhloo et al., (2011) were noted to have similar participant response rates.

5.1.1 Missing Data

Missing data denotes the absence of values for one or more variables in the dataset (Crestwell, 2012). The occurrence of missing data can be for multiple reasons, for example data entry errors, non- response, or equipment malfunction (Crestwell, 2012). The results of the 57 surveys received were checked for missing data. The dataset contained two incomplete responses which were removed, leaving 55 available responses for further analysis.

5.1.2 Reverse Coding

Reverse coding is a method employed to manage questions that are worded in the opposite direction of the construct being measured. The purpose of reverse coding is to reduce response bias that could occur when participants misinterpret or answer in a socially desirable way. This particular research study did not require reverse coding of any items.

5.1.3 Outlier Analysis

Outlier analysis is the process of detecting data points that deviate significantly from the rest of the dataset

(Everitt & Hothorn, 2019). Analyzing outliers are important as they can be various reasons that they occur. Some reasons are data entry mistakes, measurement errors or genuine extreme values (Everitt & Hothorn, 2019). Outliers can be examined by using the Z-score technique which determines the relative position of a data point within the dataset. A Z-score greater than ±3 standard deviations from the mean are considered potential outliers (McClave, Benson, & Sincich, 2018). The standardized scores for the questionnaire items were analyzed for extreme values greater than ±3, however, no extreme values were detected and thus the presence of outliers is not considered problematic for the study.

5.2 Response Profile

The response profile displayed below in figure 5.1 was created to summarize the participant responses across multiple measures. To provide an answer for Research question two the following items were profiled: job title, number of years at current organisation, number of years in current role, and organisation industry sector.

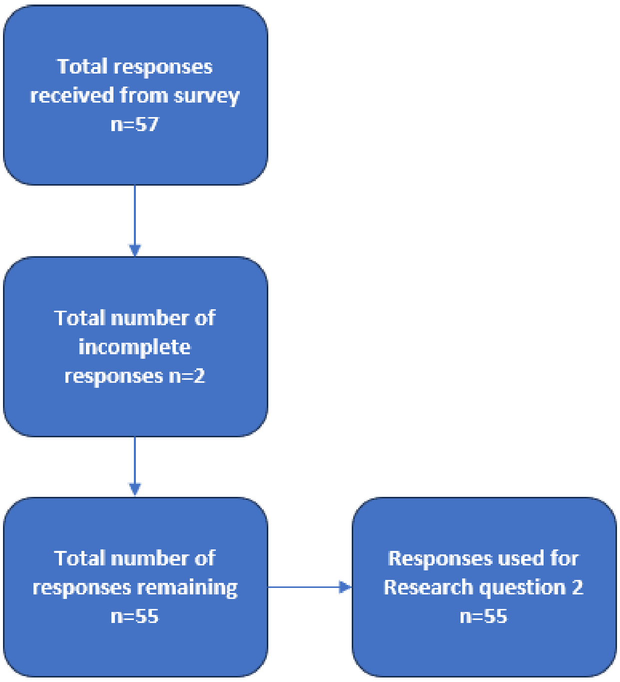

Figure 5. 1: Prism diagram describing response profile

5.2.1 Job Title of Survey Respondents

The examination of the results relating to the job title of the survey respondents highlighted that the majority of respondents were key IT decision makers for their respective organisations, with titles such as CEO, CIO, CTO, CISO, MD and Head of Technology.

Job Title	Total number of responses per job title	Percentage Total
Chief Information Officer (CIO)	11	21.9%
Chief Technology Officer (CTO)	4	7.3%
Head of Technology	5	9%
Lead Solution Architect	3	5.5%
Managing Director (MD)	2	3.6%
Chief Executive Officer (CEO)	4	7.3%
Analyst	4	7.3%
Sales Director	1	1.8%
Project Portfolio Director	2	3.6%
Head of Telecommunications	1	1.8%
Lead Engineer	1	1.8%
Director: Analytics and Systems Management	1	1.8%
Senior Data Specialist/Architect	4	7.3%
Chief Information Security Officer (CISO)	2	3.6%
Chief Operating Officer	1	1.8%
Other*	9	16.4%
Total	55	100%

* The other classification consists of human resources IT, account executives and business development directors

Table 5. 1: Job Title of respondents

5.2.2 Number of Years at Current Organisation

The respondent's number of years at their current organisation is revealed in the table below. 32.7% of respondents were at their current organisation for a duration of five to seven years, while 21.8 % for two to four years and 18.2 % for ten years or more. Respondents in all categories were deemed suitable for the research study.

Years at current organisation	Total number of responses per years at current organisation	Percentage Total
0 – 1 year	8	14.5%
2 – 4 years	12	21.8%
5 – 7 years	18	32.7%
8 – 10 years	7	12.7%
10 years +	10	18.2%

Total	55	100%

Table 5. 2: Number of years at current organisation

5.2.3 Number of Years in Current Job Role

As shown in the table below, most respondents were in their current job role for two to four years. The lowest representation was the eight-to-ten-year category of 7.3%. All 55 respondents were deemed suitable for the research study.

Years in current job role	Total number of responses per years in current job role	Percentage Total
0 – 1 year	6	10.9%
2 – 4 years	19	34.5%
5 – 7 years	18	32.7%
8 – 10 years	4	7.3%
10 years +	8	14.5%
Total	55	100%

Table 5. 3: Number of years in current job role

5.2.4 Respondents by Industry Sector

The industry sectors of responding organisations are presented in the table below. Of the eight (8) industries listed, most respondents formed part of the technology sector (32.7%), while the financial institutions sector represented 29.1% of respondents. The remaining respondents formed part of the retail, mining, basic materials, telecommunications, industrial, FinTech, education, transport, and logistics sector.

Respondent's organisation industry sector	Total number of responses per respondent's organisation industry sector	Percentage Total
Technology	18	32.7%
Retail Industry	5	9.1%
Basic Materials	2	3.6%
Oil & Gas	0	0
Mining	3	5.5%
Financial Institution	16	29.1%
Industrial	1	1.8%
Telecommunication	3	5.5%
Other	7	12.7%

Consulting	1	1.8%
Fintech	1	1.8%
Higher Education	1	1.8%
Transport and Logistics	2	3.6%

Table 5. 4: Respondents organisation industry

5.2.5 Summary of Section A: Demographics

From the responses analyzed in the demographic section of the survey, it is evident that the sample has representation from various industries in South Africa. The majority of the respondents are key IT decision makers in their organisations with most being with their organisation between five and seven years. All 55 responses were thus utilized to address Research question two for the objective of understanding current and future AI adoption.

5.3 Current State of Artificial Intelligence Adoption in South African Organisations

The pre-test performed in chapter 4 supported the study with identifying the suite of AI technologies relevant for adoption in South African organisations. Specifically, the AI technologies identified for inclusion in the survey were Machine Learning (ML), Natural Language Processing (NLP), Neural Networks (NN), Robotics Process Automation (RPA), Chatbots and Virtual Assistants, Image Recognition, and Speech Recognition.

The respondents were asked to state which of these AI technologies they had adopted and the year of adoption, plan to adopt within the next 5 years, or had no plans to adopt. The tables and graphs displayed below describe the responses received from the survey. RPA was the most adopted technology amongst the South African organisations at 58.2%, machine learning followed at 54.5% and image recognition at 50.9%. NLP and speech recognition had lower adoption statuses with 36.4% and 27.3% respectively.

Current State of Adoption	**Machine Learning (ML)**	**Natural Language Processing (NLP)**	**Neural Networks (NN)**	**Robotics Process Automation (RPA)**	**Chatbots| Virtual Assistants**	**Image Recognition**	**Speech Recognition**
Yes, already adopted	54.5%	36.4%	41.8%	58.2%	49.1%	50.9%	27.3%
Not yet adopted, but we have plans to adopt within the next 1-3 years	25.5%	25.5%	14.5%	12.7%	27.3%	14.5%	30.9%
Not yet adopted, but we have plans to adopt	10.9%	18.2%	16.4%	7.3%	10.9%	10.9%	16.4%

within the next 3-5 years							
No plans to adopt	7.3%	16.4%	21.8%	18.2%	12.7%	18.2%	21.8%
Unsure	1.8%	3.6%	5.5%	3.6%	0%	5.5%	3.6%

Table 5. 5: AI technology current state of adoption

AI technologies seem to have the highest levels of adoption among respondents from the technology and financial industries. Highest adoption rates in machine learning and image recognition are observed for the technology industry. While the financial industry has a high adoption rate of RPA, chatbots and image recognition. Adoption in retail and telecommunication sectors is lagging somewhat behind financial and technology sectors, while organisations in sectors such as mining, oil and gas, materials, and industrial are at the very nascent stages of AI adoption.

Industry	**Machine Learning (ML)**	**Natural Language Processing (NLP)**	**Neural Networks (NN)**	**Robotics Process Automation (RPA)**	**Chatbots| Virtual Assistants**	**Image Recognition**	**Speech Recognition**
Technology	20%	14.5%	16.4%	14.5%	16.4%	20%	12.3%
Retail Industry	5.5%	0%	3.6%	7.3%	5.5%	1.8%	1.8%
Basic Materials	1.8%	1.8%	0%	1.8%	1.8%	0%	0%
Oil and gas	0%	0%	0%	0%	0%	0%	0%
Mining	3.6%	0%	3.6%	3.6%	0%	3.6%	0%
Financial Institution	14.5%	14.5%	12.3%	25.5%	18.1%	18.1%	5.5%
Industrial	1.8%	0%	0%	1.8%	0%	1.8%	0%
Telecommunication	5.5%	5.5%	3.6%	3.6%	3.6%	3.6%	3.6%
Other	1.8%	0%	3.6%	0%	3.6%	1.8%	1.8%

Table 5. 6: Current state of adoption by industry

The technology adoption life cycle is a common reference when describing adoption of a technology. The five stages of adoption are innovators, early adopters, early majority, late majority, and laggards (Gruenhagen & Parker, 2020). The s-curves presented below describe the gradual growth of adoption for each of the AI technologies.

The initial stage of the s-curve has a shallow slope, that indicates slow growth or adoption. This usually represents the introduction of a new technology on the market, where only a small number of innovators or early adopters start utilizing it.

As adoption increases, the s-curve transitions to a steep growth phase. This represents adoption by the early majority and late majority adopters. The curve eventually reaches its peak, and the growth rate starts to slow down. This occurs when most potential adopters have adopted the technology and the remaining markets are resistant to change or have limited interest in adoption.

5.3.1 Machine Learning

Machine learning adoption has been on an increase with a 54.5% adoption rate. The curve below shows that the rate of adoption will reach its peak in the next three to five years and eventually start slowing down. 25.5% of the respondents reported that they are likely to adopt machine learning in the next one to three years, with 10.9% in the next three to five years.

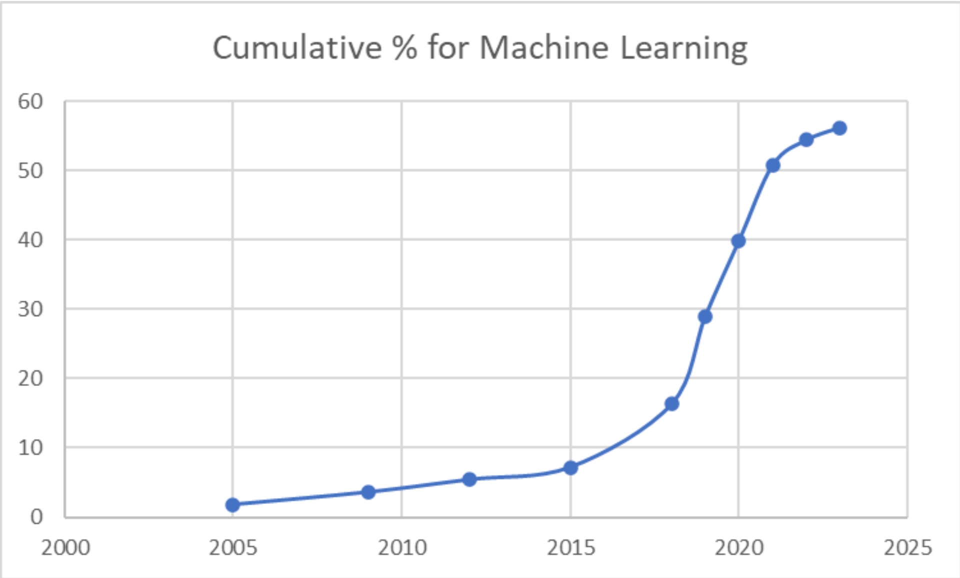

Figure 5. 2: Machine learning s-curve

5.3.2 Natural Language Processing

Natural language processing was one of the AI technologies with a low adoption rate of 36.4%. The curve below indicates that adoption is stabilizing. 25.5% of the respondents indicated that they have plans to adopt in the next one to three years, 18.2% in the next three to five years and 16.4% with no plans to adopt.

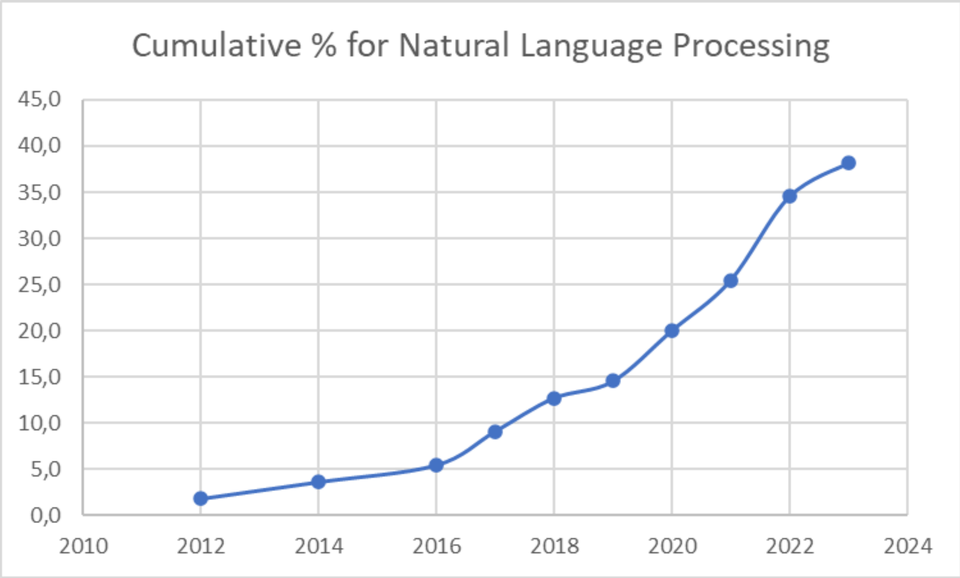

Figure 5. 3: NLP s-curve

5.3.3 Neural Networks

Neural Network adoption is on the rise with 41.8% adoption. The responses received described that adoption should increase by 31% in the next five years and stabilize thereafter with 21.8% of respondents reporting no plans to adopt.

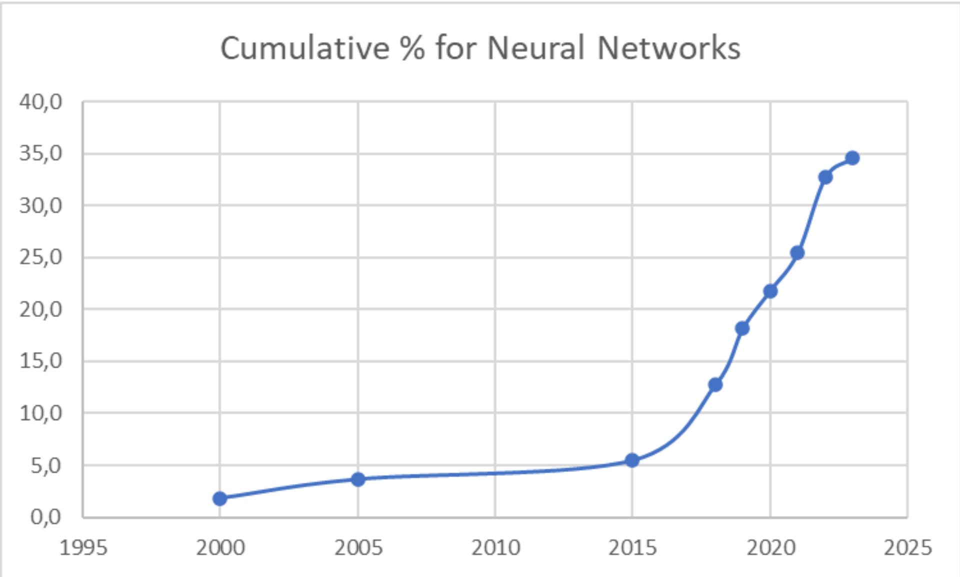

Figure 5. 4: Neural networks s-curve

5.3.4 Robotic Process Automation

RPA adoption was the highest of AI technologies adopted by the various South African industries. With only 18.2% of organisations with no plans to adopt, RPA has yet to peak along the s-curve, before flattening out.

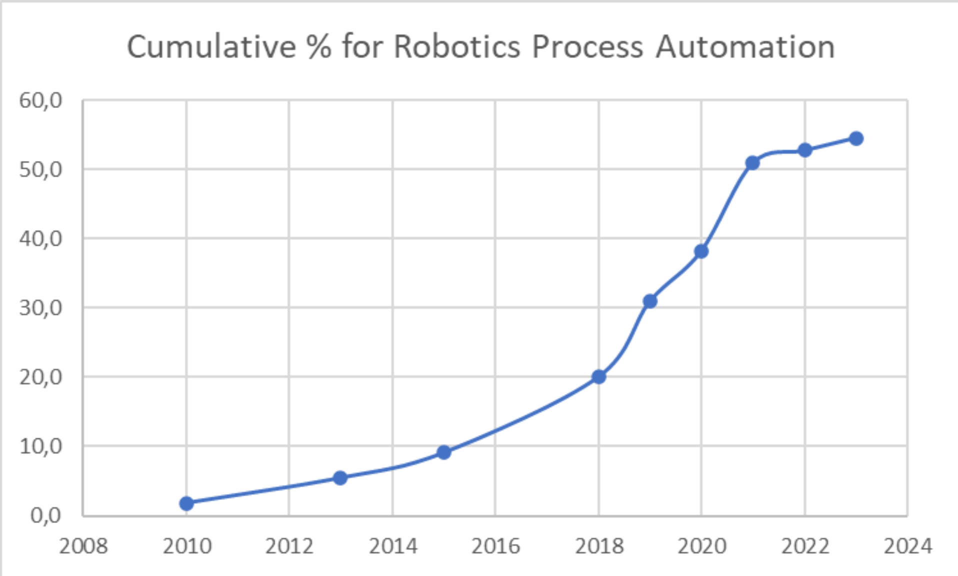

Figure 5. 5: RPA s-curve

5.3.5 Chatbots | Virtual Assistants

After just 10 years, chatbots and virtual assistants have been adopted by 49% of responding firms, with 38% of firms likely to adopt within the next five years. As depicted on the chart below, rapid rate of adoption occurred between 2016 – 2021.

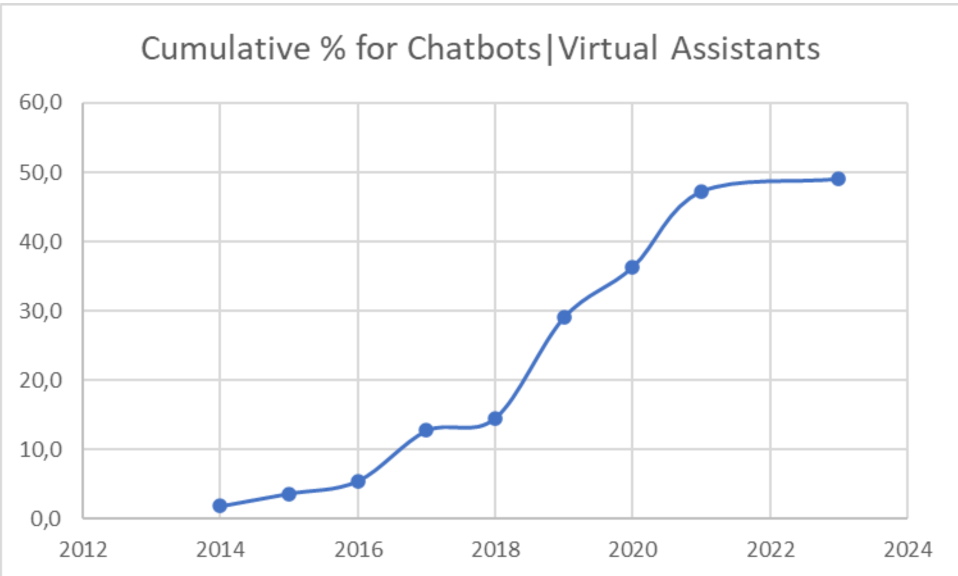

Figure 5. 6: Chatbots| Virtual Assistants s-curve

5.3.6 Image Recognition

Image recognition has been adopted already by 50.9% of sampled organisations. The highest growth rate occurred from 2019 onwards. The s-curve suggests the technology is yet to reach its peak with a further quarter of sample firms having plans to adopt in the next 5 years.

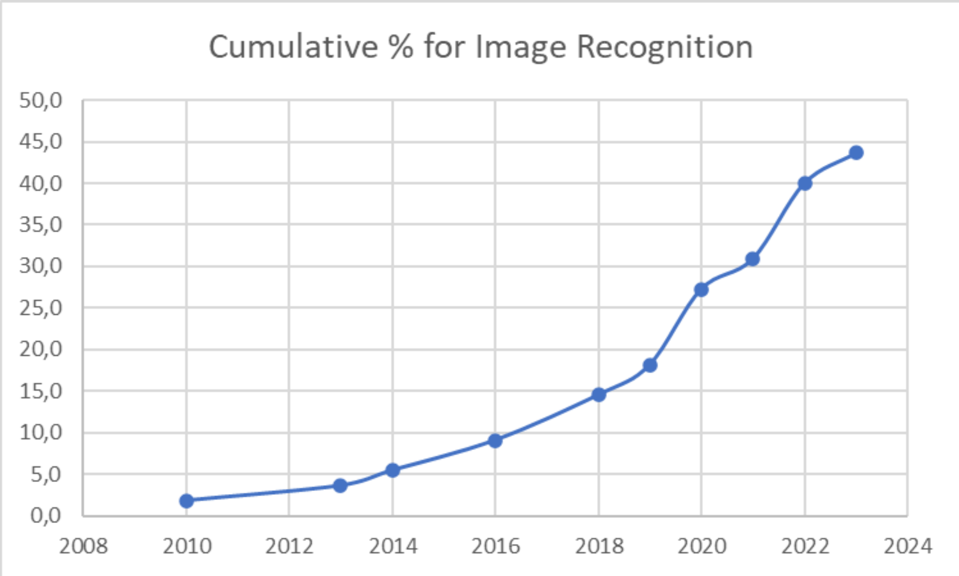

Figure 5. 7: Image recognition s-curve

5.3.7 Speech Recognition

Speech Recognition has had the lowest level of adoption at just 27.3% of sampled organisations. Growth in adoption is predicted at 30.9% between the next one to three years and by 16.4% between the next three to five years. 21.8% of respondents reported that their organisation has no plans to adopt speech recognition.

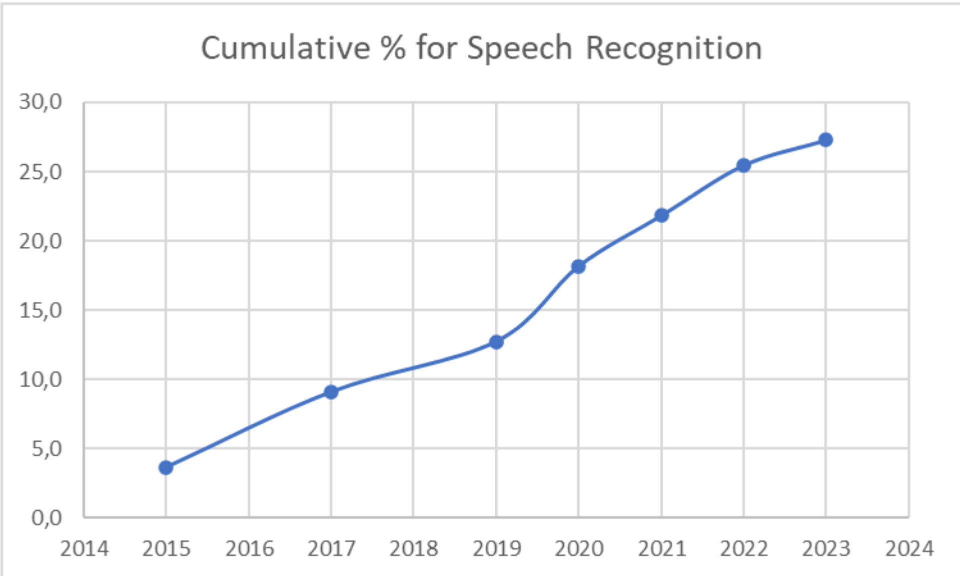

Figure 5. 8: Speech recognition s-curve

The next section of the chapter presents results of validity and reliability tests prior to testing hypotheses pertaining to the TOE factors influencing organisational AI adoption.

5.4 Research question two: TOE Factors That Influence Adoption of AI Technology

5.4.1 Validity and Reliability

Validity refers to the extent to which a study measures what it intends to measure. It examines whether the research design and methods effectively address the research question and hypothesis. Principal component analysis (PCA) is a statistical technique applied to determine dimensionality reduction and data exploration. PCA verifies if the variable in the study demonstrates unidimesionality. Unidimesionality denotes that a set of observed variables or items in a measurement instrument represents a single underlying construct, proving convergent validity. PCA can also exhibit discriminant validity by demonstrating that variables can assert low cross loadings on items that are not intended for measure.

To assess the suitability of the data the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were used.

5.4.1.1 Artificial Intelligence Technology Adoption

KMO results closer to 1 indicate a better fit for factor analysis. The KMO value obtained was 0.695 and the Bartlett's test value was significant ($p < 0.001$). This indicated that the data was suitable for factor analysis.

Principal component analysis for the dependent variable adoption is displayed below. The results displayed below indicate that all variables loaded strongly on component one. This means that one – dimensionality and convergent validity were exhibited. The total variance explained was 83.87%, which meant that convergent validity was achieved.

	Component 1
A_1	0.806
A_2	0.909
A_3	0.801

Table 5. 7: PCA of AI technology adoption

5.4.1.2 Technological Factors

Factor analysis was deemed appropriate for the study and the KMO value was 0.773 and the Bartlett's test was rendered significant ($p < 0.001$). All variables loaded well onto the component and were kept for the study. Results are shown in the table below. The total variance explained was 69.74% meeting the requirement for convergent validity.

	Component		
	Perceived Technology Benefits	**IT Infrastructure**	**Data Availability**
PTB_1	0.880		
PTB_2	0.853		
PTB_3	0.729		
ITF_1		0.611	
ITF_2		0.731	
ITF_3		0.736	
DA_1			0.521
DA_2			0.659
DA_2			0.55

Table 5. 8: PCA of Technological Factors

5.4.1.3 Organisational Factors

Factor analysis and convergent validity were deemed acceptable for the research study as the KMO result was 0.771, the Bartlett's test was significant at a p-value of $p < 0.001$ and total variance explained was 77.52%. The total variance is deemed appropriate when the value is 60% and above. All three variables loaded strongly on the component and no items were dropped.

	Component		
	Top Management Support	**Financial Resources**	**Resource Capability**
TMS_1	0.791		
TMS_2	0.854		
TMS_3	0.823		
FR_1		0.858	
FR_2		0.889	
FR_3		0.576	
RC_1			0.779
RC_2			0.774
RC_3			0.632

Table 5. 9: PCA of organisational factors

5.4.1.4 Environmental Factors

The value for KMO was 0.848 and the Bartlett's test measure was significant at $p < 0.001$. Hence, factor analysis was applicable for the research study. The total variance was above 60% and had a value of 81.05%. Convergent validity was verified. The environmental variables loaded strongly onto the component and were kept for the study.

	Component	
	Competitive Pressure	**Normative Pressure**
C_1	0.730	
C_2	0.938	
C_3	0.939	
C_4	0.932	
N_1		0.781
N_2		0.808
N_3		0.713
N_4		0.643

Table 5. 10: PCA of environmental factors

5.4.2 Reliability Measurement – Cronbach's Alpha

Since discriminant validity and convergent validity was established for the variables, the reliability was measured using Cronbach's alpha. The acceptable scores for internal consistency should be above 0.7. The corrected item to total correlation score is deemed acceptable at 0.4 and above. All the variables below were above 0.7 and considered acceptable for the research study.

Variable	Cronbach's Alpha	Items per Variable	Standard Deviation	Mean	Corrected Item – Total Correlation
AI Adoption	0.903	3	1.697	4.273	0.773
					0.885
					0.769
Perceived Technology Benefits	0.890	3	1.347	5.7273	0.832
					0.869
					0.680
IT Infrastructure	0.877	3	1.464	4.781	0.754
					0.794
					0.768

Data Availability	0.755	3	1.319	5.121	0.609
					0.541
					0.565
Top Management Support	0.964	3	1.343	5.488	0.892
					0.949
					0.934
Financial Resources	0.853	3	1.226	5.091	0.811
					0.859
					0.551
Resource Capability	0.915	3	1.704	3.976	0.822
					0.873
					0.794
Competitive Pressure	0.953	4	1.418	4.588	0.768
					0.930
					0.927
					0.932
Normative Pressure	0.871	4	1.316	4.086	0.769
					0.766
					0.732
					0.650

Table 5. 11: Results showing reliability using Cronbach's alpha

5.4.2.1 Correlation Analysis

Subsequent to PCA and reliability tests, correlation analysis was performed. Composites scores were calculated for each of the variables as the arithmetic averages of their measurement items. Since the study encompassed interval and ratio measures, Pearson correlation was applied. Pearson's correlation coefficient is a statistical measure that quantifies the strength and direction of the linear relationship between two variables. The direction of the linear relationship can be positive or negative. Spearman correlation focuses on the rank order of the data and is displayed below.

	Pearson Correlation (with Artificial Intelligence Adoption)	**Spearman Correlation (with Artificial Intelligence Adoption)**
Perceived Technology Benefits	0.314*	0.202
IT Infrastructure	0.537**	0.558**
Data Availability	0.668**	0.607**
Top Management Support	0.542**	0.508**

Financial Resources	-0.085	-0.177
Resource Capability	0.535**	0.577**
Competitive Pressure	0.075	0.182
Normative Pressure	0.319*	0.368**

Table 5. 12: Correlation results **p < 0.01 *p < 0.05 (n = 55)

Hypothesis 1

With use of Pearson correlation, the association between perceived technology benefits (mean = 5.727; standard deviation = 1.347) and AI technology adoption (mean = 4.273; standard deviation = 1.697) was examined. The results revealed a statistically significant correlation between these variables ($r = 0.314$; $p < 0.05$). This result supports hypothesis 1, indicating a positive and significant relationship between perceived technology benefits and AI technology adoption. Accordingly, the greater the perceived benefits of AI technology, the greater the likelihood of adoption. The Spearman correlation also confirms the significant association between perceived technology benefits and AI technology adoption (rho = 0.202; $p < 0.05$).

Hypothesis 2

With use of Pearson correlation, the association between IT infrastructure (mean = 4.781; standard deviation = 1.464) and AI technology adoption (mean = 4.273; standard deviation = 1.697) was examined. The results revealed a statistically significant correlation between these variables ($r = 0.537$; $p < 0.01$). This result supports hypothesis 2, indicating a positive and significant relationship between IT infrastructure and AI technology adoption. Accordingly, the greater the availability of advanced information technology infrastructure for AI technology, the greater the likelihood of adoption. The Spearman correlation confirms the significant association between IT infrastructure AI technology adoption (rho = 0.558; $p < 0.01$).

Hypothesis 3

With use of Pearson correlation, the relationship between data availability (mean = 5.121; standard deviation = 1.319) and AI technology adoption (mean = 4.273; standard deviation = 1.697) was examined. The results revealed a statistically significant correlation between these variables ($r = 0.668$; $p < 0.01$). This result supports hypothesis 3, indicating a positive and significant relationship between data availability and AI technology adoption. Accordingly, the greater the availability of good quality data for AI technology, the greater the likelihood of adoption. The Spearman correlation confirms the significant association between data availability and AI technology adoption (rho = 0.607; $p < 0.01$).

Hypothesis 4

With use of Pearson correlation, the relationship between top management support (mean = 5.488; standard deviation = 1.343) and AI technology adoption (mean = 4.273; standard deviation = 1.697) was examined. The results revealed a statistically significant correlation between these variables ($r = 0.542$; $p < 0.01$). This result supports hypothesis 4, indicating a positive and significant relationship between top management support and AI technology adoption. Accordingly, the greater the support from top management, the greater the likelihood of adoption. The Spearman correlation confirms the significant association between top management support and AI technology adoption ($rho = 0.508$; $p < 0.01$).

Hypothesis 5

With use of Pearson correlation, the relationship between financial resources (mean = 5.091; standard deviation = 1.226) and AI technology adoption (mean = 4.273; standard deviation = 1.697) was examined. The results revealed a non-significant correlation between the variables ($r = -0.085$; $p > 0.05$). Therefore, the results do not provide support for hypothesis 5, AI technology adoption is not dependent on financial resources and therefore hypothesis 5 (the greater the financial resources required for AI technology, the lesser the likelihood of adoption.) is rejected. The Spearman correlation was also non-significant ($rho = -0.177$; $p > 0.05$).

Hypothesis 6

With use of Pearson correlation, the relationship between resource capability (mean = 3.976; standard deviation = 1.704) and AI technology adoption (mean = 4.273; standard deviation = 1.697) was examined. The results revealed a statistically significant correlation between these variables ($r = 0.535$; $p < 0.01$). This result supports hypothesis 6, indicating a positive and significant relationship between resource capability and AI technology adoption. Accordingly, the greater the AI technology resource capability within South African organisations, the greater the likelihood of adoption. The Spearman correlation confirms the significant association between resource capability and AI technology adoption ($rho = 0.577$; $p < .001$).

Hypothesis 7

With use of Pearson correlation, the relationship between competitive pressure (mean = 4.588; standard deviation = 1.418) and AI technology adoption (mean = 4.273; standard deviation = 1.697) was examined. The results revealed a non-significant correlation between the variables ($r = 0.075$; $p > 0.05$). Therefore, the results do not provide support for hypothesis 7, AI technology adoption is not dependent on competitive pressure. Therefore, hypothesis 7 (organisations experiencing high levels of competitive pressure are more likely to adopt AI technology) was rejected. The Spearman correlation was also non-significant ($rho = 0.182$; $p > 0.05$).

Hypothesis 8

With use of Pearson correlation, the relationship between normative pressure (mean = 4.086; standard deviation = 1.316) and AI technology adoption (mean = 4.273; standard deviation = 1.697) was examined. The results revealed a statistically significant correlation between these variables ($r = 0.319$; $p < 0.05$). This result supports hypothesis 8, indicating a positive and significant relationship between normative pressure and AI technology adoption. Accordingly, organisations experiencing high levels of normative pressure are more likely to adopt AI technology. The Spearman correlation confirms the significant association between normative pressure and AI technology adoption ($rho = 0.368$; $p < .001$).

5.4.3 Multiple Regression

Although bivariate correlation analysis is helpful, it does not support combined or cumulative effects of independent variables on the dependent variables. Multiple regression was used to achieve this.

5.4.3.1 Technological Factors

The first multiple regression test performed was with the independent variables of perceived technology benefits, IT infrastructure, and data availability, and the dependent variable adoption. These factors had the following hypothesis:

H1: The greater the perceived benefits of AI technology, the greater the likelihood of adoption.

H2: The greater the availability of advanced information technology infrastructure for AI technology, the greater the likelihood of adoption.

H3: The greater the availability of good quality data for AI technology, the greater the likelihood of adoption.

Model Summary				
Model	**R**	**R square**	**Adjusted R square**	**Std error of estimate**
1	.687 [a]	.472	.441	1.26856
Predictors: (Constant), perceived technology benefits, IT infrastructure, data availability				

Table 5. 13: Summary of multiple regression – Technological factor

ANOVA[a]						
Model		**Sum of squares**	**df**	**Mean square**	**F**	**Sig.**
1	Regression	73.504	3	24.501	15.225	<, 001[b]
	Residual	82.072	51	1.609		
	Total	155.576	54			
a. Dependent variable: Adoption						
b. Predictors: (Constant), perceived technology benefits, IT infrastructure, data availability						

Table 5. 14: ANOVA – Technological factor

Coefficients[a]						
Model		**Unstandardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
		B	**Std error**	**Beta**		
1	(Constant)	-.536	.878		-.064	.524
	Perceived technological benefits	.041	.151	.032	.270	.788
	IT infrastructure	.241	.166	.184	1.283	.205
	Data availability	.699	.166	.544	4.209	< ,001
a. Dependent variable: AI technology adoption						

Table 5. 15: Coefficient – Technological Factor

The R^2 value is 47.2%. This suggests that the model accounts for approximately 47% of the variation in AI technology adoption. This outcome holds significance at the $p < 0.001$ level.

Data availability (independent variable) has the greatest significant outcome on AI technology adoption. The variable has a standardized coefficient of .544, which is significant at the $p < 0.001$ level. The other predictor variables have non-significant effects. This does not mean that those variables are unimportant. What it means is that from a statistical point of view, the variables perceived technology benefit and IT infrastructure do not add significantly to our prediction of success beyond data availability even though strong correlation results were reported in table 5.11 above.

Additional support is provided for hypothesis 3 through the results generated from the multiple regression analysis.

5.4.3.2 Organisational Factors

Using the TOE framework as a lens, the organisational factors of top management support, financial cost, and resource capability were included as the independent variables for the next multiple regression test with AI technology adoption as the dependent variable. The hypotheses were stated as follows:

H4: The greater the support from Top Management, the greater the likelihood of adoption.

H5: The greater the financial resources required for AI technology, the lesser the likelihood of adoption.

H6: The greater the AI technology resource capability within South African organisations, the greater the likelihood of adoption.

Model Summary				
Model	**R**	**R square**	**Adjusted R square**	**Std error of estimate**
1	.599[a]	.358	.320	1.37816
a. Predictors: (Constant), top management support, financial cost, resource capability				

Table 5. 16: Summary of multiple regression – Organisational factor

ANOVA[a]						
Model		**Sum of squares**	**df**	**Mean square**	**F**	**Sig.**
1	Regression	53.034	3	17.678	9.308	< ,001[b]
	Residual	94.966	50	1.899		
	Total	148.000	53			
a. Dependent variable: Adoption						
b. Predictors: (Constant), top management support, financial cost, resource capability						

Table 5. 17: ANOVA – Organisational factor

Coefficients[a]						
Model		**Unstandardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
		B	Std error	Beta		
1	(Constant)	1.910	1.067		1.789	.080
	Top management support	.464	.207	.373	2.239	< ,001
	Financial cost	-.246	.155	-.182	-1.590	.118

	Resource capability	.258	.163	.263	1.583	.120
a. Dependent variable: AI technology adoption						

Table 5. 18: Coefficient – Organisational factor

The R^2 value is 35.8%. This suggests that the model accounts for approximately 36% of the variation in AI technology adoption. This outcome holds significance at the $p < 0.001$ level.

Top management support (independent variable) has the greatest significant outcome on AI technology adoption. The variable has a standardized coefficient of .373, which is significant at the $p < 0.001$ level. The other predictor variables have non-significant effects. What this means is that from a statistical point of view, the variables financial cost and resource capability do not add significantly to our prediction of success.

Additional support is provided for hypothesis 4 through the results generated from the multiple regression analysis. Top management support is vital for adoption to occur.

5.4.3.3 Environmental Factors

The third multiple regression test considered the environmental factors of the TOE framework. The independent variables that were part of the analysis were competitive pressure and normative pressure, with the dependent variable being AI technology adoption. The hypotheses were as follows:

H7: Organisations experiencing high levels of competitive pressure are more likely to adopt AI technology.

H8: Organisations experiencing high levels of normative pressure are more likely to adopt AI technology.

Model Summary				
Model	**R**	**R square**	**Adjusted R square**	**Std error of estimate**
1	.363[a]	.132	.098	1.61188
a. Predictors: (Constant), competitive pressure, normative pressure				

Table 5. 19: Summary of multiple regression – Environmental factors

ANOVA[a]						
Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	20.472	2	10.236	3.940	.026[b]
	Residual	135.104	52	2.598		
	Total	155.576	54			
a. Dependent variable: Adoption						
b. Predictors: (Constant), competitive pressure, normative pressure						

Table 5. 20: ANOVA - Environmental factors

Coefficients[a]						
Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std error	Beta		
1	(Constant)	3.070	.797		3.850	<,001
	Competitive pressure	-.273	.203	-.228	-1.342	.185
	Normative pressure	.602	.219	.467	2.746	.008
a. Dependent variable: AI technology adoption						

Table 5. 21: Coefficient - Environmental factors

The R^2 value is 13.2%. This suggests that the model accounts for approximately 13% of the variation in AI technology adoption. This outcome holds significance at the $p < 0.001$ level.

Normative pressure has a significant effect on AI technology adoption, at the $p<0.01$ level. This suggests normative pressure is the more important external factor driving AI adoption among the sample organisations.

5.4.3.4 Stepwise Multiple Regression (All Independent Variables)

The multiple regression analysis generated insights about the Technology, Organisation and Environment (TOE) factors that are most significant for AI technology adoption. The next step of the analysis provides insights into the combined relative affects of the TOE factors having the largest effects on adoption as determined by the step-wise regression procedure.

Model Summary				
Model	R	R square	Adjusted R square	Std error of estimate
1	.654[a]	.427	.416	1.27692

2	. 714b	.510	.419	1.191199
a. Predictors: (Constant), data availability				
b. Predictors: (Constant), data availability, top management support				

Table 5. 22: Summary of stepwise regression – All TOE factors

ANOVA[a]						
Model		**Sum of squares**	**Df**	**Mean square**	**F**	**Sig.**
1	Regression	63.213	1	63.213	38.768	< ,001[b]
	Residual	84.787	52	1.631		
	Total	148.000	53			
	Regression	75.537	2	37.768	26.582	< ,001[c]
	Residual	72.463	51	1.421		
	Total	148.000	53			
a. Dependent variable: AI technology adoption						
b. Predictors: (Constant), data availability						
c. Predictors: (Constant), data availability, top management support						

Table 5. 23: ANOVA – Stepwise regression

Coefficients[a]						
Model		**Unstandardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
		B	**Std error**	**Beta**		
1	(Constant)	-.029	.705		-.041	.967
	Data availability	.836	.134	.654	6.226	< ,001
2	(Constant)	-1.316	.790		-1.666	.102
	Data availability	.660	.139	.516	4.753	< ,001
	Top management support	.398	.135	.320	2.945	.005
a. Dependent variable: AI technology adoption						

Table 5. 24: Coefficient – Stepwise regression

The results from the stepwise regression analysis evidence the importance of data availability a technological factor and top management support an organisational factor with explained variance of 51%. Therefore, these two factors of the model explains roughly 51% of the AI technology adoption variance.

Chapter 5: Conclusion

The results from the survey were interpreted in this chapter. A detailed summary was provided about the various aspects of analysis that the data underwent, i.e., data screening, identifying missing values, and reverse scoring. The state of AI technology adoption for each of the technologies was also highlighted through the use of s-curves. RPA was the AI technology with the highest level of current adoption. The TOE framework factors that grounded research question two were then tested for effects on AI adoption. The set of factors explored overcame the limitations of prior studies as summarised in chapter two. Pearson and Spearman tests, multiple and stepwise regression analysis were used to test the hypotheses. The table below offers a summary of the correlation, multiple and stepwise regression results. Only H5 (financial costs) and H7 (competitive pressure) are rejected for having no significant correlation with adoption, while the factors having the most significant effects on AI adoption were H3 (data availability) and H2 (top management support).

Hypothesis	**Correlation Results**	**Multiple Regression Results**	**Stepwise regression results**
H1: Perceived technology benefit	Supported		
H2: IT infrastructure	Supported		
H3: Data availability	Supported	Supported	Supported
H4: Top management support	Supported	Supported	Supported
H5: Financial cost	Not supported		
H6: Resource capability	Supported		
H7: Competitive pressure	Not supported		
H8: Normative pressure	Supported	Supported	

Table 5. 25: Summary of correlation and regression

Chapter 6: Discussion of Results

This chapter discussed the results pertaining to Research question one and Research question two in relation to the current literature. Section one presents a discussion on the current state of adoption of the suite of AI technologies identified for inclusion in the study (Research question one). Secondly, the results of the test of the TOE model are discussed (Research question two).

6.1 Research question one: Suite of Artificial Intelligence Technologies

Research question one in the study states: What types of Artificial Intelligence technologies are used by South African organisations? To provide an answer to this research question a systematic literature review was first conducted. Analyzing literature on AI studies generated a list of technologies to present to a panel of experts in the pre – test phase to confirm if these technologies are being used in various sectors of South African organisations. Presented below is a list of AI technologies that were established as relevant for organisations:

1. **Machine learning**

Machine learning focuses on providing self-learning capabilities to computers and systems to adapt and improve through experiences without the need for explicit programming (Donepudi, 2017; KPMG, 2020). An example of machine learning is analysing of customer data to provide targeted marketing to increase purchasing behavior (Columbus, 2018; Global, 2018).

2. **Natural language processing**

The objective of natural language processing is to support computers to comprehend, analyze and generate human language in a manner that is both meaningful and beneficial (Grguric, Vlacic, & Drvenkar, 2020). The financial industry uses NLP to extract information from forms for more accurate and efficient processing (Boitnott, 2020).

3. **Neural Networks**

Neural networks were conceptualized from the structure and formation of the human brain. It is made up of units that are arranged in layers to process and learn from input data (Benbya, Pachidi, & Jarvenpaa, 2021). The manufacturing industry uses neural networks to detect abnormalities or defects in their processes or to predict equipment failure (Columbus, 2018). The transportation industry makes use of neural networks for safe route navigation (Pruciak, 2021).

4. Robotics Process Automation

RPA is software that is governed by rules to mimic human actions (Dirican, 2015). The mining industry uses RPA to automate regulatory tasks such as data gathering and compliance reports ensuring adherence to regulatory requirements (Dirican, 2015).

5. Chatbots | Virtual Assistance

Chatbots are system programs used to simulate human conversation and interact with humans in a conversational manner (Hradecky, Kennell, Cai, & Davidson, August 2022). Chatbots are used in the finance industry to assist everyday banking customers with personal finance management by generating personalized tips on budgeting, spend patterns and expenditure tracking (Doherty & Curran, 2019).

6. Image Recognition

Image recognition uses algorithms to identify and classify objects or patterns (Kabalisa & Altmann, 2021). The retail industry uses image recognition to optimize their inventory management by monitoring stock on shelves by analyzing images and videos (Matallanas, 2022).

7. Speech Recognition

Speech recognition converts human speech into text. The automotive industry uses speech recognition for voice activated commands such as making a phone call, adjusting the temperature, and switching radio stations.

Interestingly, large language models and technologies such as ChatGPT were not surfaced at the time this research was conducted. Large language models and ChatGPT are defined as a class of generative AI that is designed to engage in text-based conversations (Alberts, Mercolli, & Pyka, 2023). They may have potential uses such as natural language processing tasks, text generation and language translation, future research should explore those further (Alberts et al., 2023).

6.1.1 Current State of Artificial Intelligence Adoption in SA Organisations.

To further inform Research question two, respondents to the main survey were requested to indicate which of the AI technologies were adopted in their business area and the year of adoption. The data collected revealed that at least 88% of the respondent’s business units have adopted one or more AI technologies from the pre - defined list.

The s-curve by Rogers (2010) was used to depict the level of adoption for each AI technology. The data revealed that RPA and machine learning were the most adopted of the suite of technologies. Image recognition and neural networks closely followed. Chatbots or virtual assistants showed a significant increase in adoption between 2018 – 2021. One of the more common reasons for the increase in chatbot adoption is the need to service clients at any hour of the day, chatbots provide that flexibility for industries (Ameer-Mia, Pienaar, & Kekana, 2020). There was positive feedback from the responses received that indicated that the rate of adoption for all technologies on the list will increase in the next one to five years for South African organisations.
The technology with the lowest adoption rate was speech recognition. The data indicated that speech recognition adoption will increase in the next one to three years by approximately 31% across the industries. The advancements in machine learning and neural networks were reported to have an impact on the increase of speech recognition adoption (Ammanath, 2022). NLP has a similar adoption trend. Industries were initially slow to adopt with the current adoption rate from the responses received being 36.4%. However, with the improvements and availability of data, NLP adoption is likely to increase by 25.5% as revealed from the data collected (Ammanath, 2022). The summary of the rate of AI technology adoption as presented in table 5.5 above.

Robotics Process Automation (RPA)	58.2%
Machine Learning	54.5%
Image Recognition	50.9%
Chatbots | Virtual Assistance	49.1%
Neural Networks	41.8%
Natural Language Processing (NLP)	36.4%
Speech Recognition	27.3%

The current state of adoption for AI varies across industries and organisations. Over the years, AI has gained significant attention and has been increasingly adopted in various sectors. Past studies (Alsheibani, Cheung, & Messom, 2018; Benbya, Davenport, & Pachidi, 2020; Digalaki, 2021; Filipe, Ruivo, & Oliveria, 2023) mentioned also found importance in understanding current state of adoption for technologies being studied. This is because the state of AI adoption is dynamic with advancements occurring swiftly and it is important for organisations to understand how they are currently measuring within their industry.

6.2 Research question two: TOE Model

Research question two was designed to uncover the technology, organisation and environment factors that impacted adoption of AI technology in organisations. The conceptual model was built on the foundation of the TOE framework. Eight hypotheses were presented with the following variables: perceived technological benefit, IT infrastructure, data availability, top management support, financial cost, resource capability, competitive pressure, and normative pressure.

6.2.1 RQ2a: What technology factors influence adoption of AI technology in South African organisations?

6.2.1.1 Perceived technological benefit

It was hypothesized that the greater the perceived benefits of AI technology, the greater the likelihood of its adoption. The perceived technological benefits identified were (Mariemuthu, 2019):

- Identification of fraud in organisations through visualization aids
- Increased customer advantage by understanding the consumer footprint
- Increased innovation as more manual tasks are automated
- Improvement in process efficiency and turnaround times
- Reaching new clientele

The Pearson and Spearman correlation tests produced a positive significant relationship thus supporting the hypothesis for perceived technological benefits. Past studies using the TOE framework produced similar results for perceived benefits (Gutierrez, Boukrami, & Lumsden, 2015; Bhattacharya & Wamba, 2015; Mariemuthu, 2019). A study by Ma et al., 2021 suggested that organisations gain long term strategic benefits with adoption of AI technology that enables them to build better processes, gain a competitive edge and increase their customer footprint. Prior to adoption of AI technology, it is crucial to obtain a clear understanding of the benefits to guide decision making processes within the organisation.

6.2.1.2 IT Infrastructure

It was hypothesized that the greater the availability of advanced information technology infrastructure for AI technology, the greater the likelihood of AI adoption. The following measures were used for IT infrastructure (Oliveira & Martins, 2010):

- Compatibility of artificial intelligence technology with customer or supplier software
- Infrastructure in place can support AI.
- Legacy system compatibility

The Pearson and Spearman correlation tests produced a positive significant relationship thus supporting the hypothesis for IT infrastructure. Other studies (Chen, Li, & Chen, 2021; Gupta, Ghardallou, Pandey, & Sahu, 2022) that measured IT infrastructure had similar results. Compatibility with legacy systems, supplier, and customer software and sufficient IT infrastructure in place to support AI technology were all highly rated by respondents. Filipe et al., (2023) found that firms that have good infrastructure in place were more influenced to adopt new technologies than firms that lacked infrastructure development. Before embarking on an AI adoption journey, it is imperative to carefully assess the establishment of fundamental IT infrastructure to ensure compatibility of existing systems with this transformative technology.

6.2.1.3 Data availability

Data availability was a novel construct introduced for this study. It was hypothesized that the greater the availability of good quality data for AI technology, the greater the likelihood of AI adoption. Data availability was measured as (Chen, Li, & Chen, 2021; Ammanath, Jarvis, & Hupfer, 2020):

- Complete and accurate data
- Data repositories to store and process large amounts of data at an acceptable speed
- Access to data required for AI technology

The Pearson and Spearman correlation tests and multiple regression analysis confirmed that data availability was significant for adoption and stepwise regression analysis showed that data availability was the most highly supported factor for AI adoption. Data availability has become a factor that is being supported across industries and organisations (Te, Muller, Wyder, & Pramono, 2018). It has become a pre-requisite for any tasks that need to be carried out. With AI adoption on the rise, organisations are realizing the value of having good quality data. Current AI research studies (Ammanath, 2022; Uren & Edwards, 2023) using data as a measure state that without good quality (complete, accurate, timely) data the value of the above-mentioned AI technologies will not be realized. A significant amount of data is required to produce accurate and robust data models that generate valuable insights (Nguyen, Le, & Ly Vu, 2022). Organisations should ensure they have appropriate underlying data availability before embarking on AI projects.

6.2.2 RQ2b: What organisational factors influence adoption of AI technology in South African organisations?

6.2.2.1 Top Management support

Top management support was hypothesized as being important to AI adoption. This is because top management needs to drive a cohesive strategy, provide budget for resources and support organisational changes required to succeed with implementation of new technologies (Hradecky, Kennell, Cai, & Davidson, August 2022). Top management support encompassed the following (Cao, Duan, Edwards, & Dwivedi, August 2021):

- Collaborative working environment and promotion of innovation for new technologies support
- Driving the adoption of new technologies
- Investing in technology adoption to support training, infrastructure, and maintenance costs

Top management supported produced a positively significant relationship with both the correlation tests and multiple regression analysis. In the stepwise analysis, top management support was deemed as the second most significant factor for artificial intelligence technology adoption. The results produced from the analysis are consistent with past TOE studies (Chuah, Tseng, Wu, & Cheng, 2021; Wong, Leong, Hew, Tan, & Ooi, 2020; Cao, Duan, Edwards, & Dwivedi, August 2021). It is important for top management to align to AI adoption decisions for several reasons; firstly, to drive a united strategy for AI investment so that all employees in an organisation contribute towards this strategic goal (Access Partnership, 2018). Secondly, AI requires specialist skills especially at the initial adoption stage, and thus top management need to support their business areas with staffing, infrastructure upgrades and budget allocation (Accenture, 2019). Thirdly, change management is required as AI involves organisational changes, process adjustments and possible mindset changes (Gupta, Ghardallou, Pandey, & Sahu, 2022). Fourthly, top management sets the tone for leadership and cultural changes in an organisation, top management endorsement of AI will send a strong message to employees to embrace the strategic change (Du, Pan, Leidner, & Ying, 2019). Lastly, adoption of AI technology does come with certain risks and challenges, such as ethical consideration, privacy, security, and potential impacts on jobs (Ambati, Narukonda, Bojja, & Bishop, 2020). Top management support is vital in identifying these risks and establishing robust governance to mitigate any pitfalls of AI adoption decisions.

6.2.2.2 Financial Resources

The requirements for financial resources were hypothesized to be a potential inhibitor for AI technology adoption. This was expected because adoption of AI requires a substantial number of resources, IT infrastructure upgrades and maintenance which is seen as a major cost to organisations (Gartner, 2019). The measures that reflected financial resources required for AI were (Chuah, Tseng, Wu, & Cheng, 2021)

- Migration and maintenance cost
- New technology setup costs
- Resource training costs

The hypothesis was unsupported as the Pearson and Spearman correlation tests produced a weak negative correlation. Although cost to an organisation is a factor when making an IT adoption decision, it appears not to be a primary consideration in the sample studied. Instead, it appears that these organisations are more inclined to focus on benefits factors such as long-term revenue generation, competitive edge gained in the market that they operate in, future proofing their operations by staying ahead of the curve and the return on investment from the new technology adoption (Gutierrez, Boukrami, & Lumsden, 2015; Charalambous, Feldmann, Richter, & Schmitz, 2019).

6.2.2.3 Resource Capability

It was further hypothesized that the greater the AI technology resource capability within South African organisations, the greater their likelihood of AI adoption. This is because AI technology requires a unique skillset i.e., machine learning specialists, data scientists and other domain experts (Van Buren, Chew, & Eggers, 2020; Accenture, 2017). The measures that reflected resource capability were (Ambati, Narukonda, Bojja, & Bishop, 2020; Duh & Fabiao, 2018):

- Increased rate of hire for skilled AI resources
- Existing AI expertise in the organisation
- Regular AI training to keep up to date with latest industry trends

The correlation tests produced a significant positive correlation; thus, the hypothesis was accepted. Several studies (Duh & Fabiao, 2018; Bhattacharya & Wamba, 2015; Nevo & Wade, 2011) generated similar results for resource capability. Wong et al., (2020) argued that organisations avoid adopting complex technologies if they do not have the knowledge to support the technology. The results suggest this is also the case with AI technology adoption. Recognising and investing in talent development to cultivate a skilled workforce to drive AI adoption is therefore an important enabler.

6.2.3 RQ2c: What environmental factors influence adoption of AI technology in South African organisations?

6.2.3.1 Competitive Pressure

Competitive pressure was hypothesized as promoting AI adoption such that organisations experiencing high levels of competitive pressure would be more likely to adopt AI technology. This is because institutional theory suggests that firms are likely to consider adoption if other industry players are adopting AI technology to secure their position within the industry (DiMaggio & Powell, 1983). The following measures were considered for competitive pressure (Chen, et al., 2014; Krell, Matook, & Rohde, 2016):

- Pressure from competitor firms to adopt AI
- Supplier pressure to adopt AI
- Perceived benefits of AI adoption from direct competitors

The correlation results generated from the Pearson and Spearman tests were not significant. A weak positive linear relationship was identified. This was contradictory to the results produced by (Mariemuthu, 2019; Chen, Li, & Chen, 2021). However, the results were consistent with studies by Maroufkhani et al., (2022) and Nguyen et al., (2022) Reasons highlighted in these two previous studies for the unsupported hypothesis was the nature of the industry, market dynamics, organisational strategy, and availability of resources. Competitive pressure alone does not drive new technology adoption. Organisations appear more likely to take factors such as underlying infrastructure, capabilities, return on investment and long-term benefits into consideration.

6.2.3.2 Normative Pressure

Finally, it was hypothesized that organisations experiencing high levels of normative pressure would be more likely to adopt AI technology. This is because organisations experience pressure to conform to certain societal norms or industry standards (DiMaggio & Powell, 1983). The following measures reflected normative pressure (Teo, Wei, & Benbasat, 2003; Krell, Matook, & Rohde, 2016):

- Customer adoption of AI technology
- Supplier adoption of AI technology
- AI is promoted regularly through trade and industry bodies

The hypothesis was supported as a highly positive correlation was produced from the Pearson and Spearman tests. Normative pressure did produce significant effects on AI adoption from the multiple regression analysis. Other studies also found normative pressure significant for technology adoption (Filipe, Ruivo, & Oliveria, 2023; Al-Omoush, Moya, Al - ma'aitah, & Garcia, 2021; Oliveira & Martins, 2011). Preceding studies have shown that organisations do maintain social cohesion by shaping and regulating behaviors (Bahrami, Ghorbani, & Arabzad, 2012). Organisations will become more likely to adopt where the use of AI becomes a normalised and standardised expectation for firms operating within that industry sector. Industry bodies will thus need to play a large role in promoting AI adoption before it is likely to be considered and, similarly, AI adoption is less likely to occur where industry bodies caution against its adoption.

Chapter 6: Conclusion

This chapter summarized the response to Research question one by outlining the current state of adoption of AI technologies as confirmed by IT professionals in South African organisations, along with their future plans to adopt AI technology. The chapter also discussed the response to Research question two on the TOE factors that influenced adoption. All three technological factors (perceived technology benefits, IT infrastructure, data availability), two organisational factors (top management support, resource capability) and one environment factor (normative pressure) were discussed as important to adoption. Top management support and data availability were the most significant for AI adoption decisions whereas financial cost and competitive pressure did not significantly influence adoption of AI.

Chapter 7: Conclusion

This chapter summarises the research study along with its findings and highlights how the research objectives were addressed. The recommendations for practice and academia and limitations relating to this research study with recommendations for future research are also discussed.

7.1 Research Summary

Artificial intelligence (AI) refers to the formation of machines that mimic human intelligence and encompasses various technologies. AI technology is changing the landscape for South African organisations and how they operate.

The objective of this research paper was to investigate the state of AI adoption and the factors influencing AI technology adoption by South African organisations. Two research questions were posed:

- **<u>RQ1:</u>** What types of artificial intelligence technologies are used by South African organisations?

- **<u>RQ2:</u>** What TOE factors influence adoption of AI technology in South African organisations?

Firstly, to address Research question one, it was important as part of the research study to recognize a list of artificial intelligence technologies. This was accomplished through analyses of the existing literature on AI, published reports and pre – testing with key IT experts. The technologies identified through this endeavor were machine learning, neural networks, natural language processing, robotics process automation, chatbots or virtual assistants, speech, and image recognition. The above listed technologies formed the list of AI technologies used by organisations in South Africa.

Secondly, the current state of adoption of the technologies within a sample of organisations was also established. To accomplish this a survey was distributed online to 252 participants. The participants were a representation of key IT decision makers across South African industries. A total of 57 responses were received. Robotics process automation was revealed as the most adopted technology, with machine learning and natural language processing following closely. Speech recognition was recognized as the least adopted technology. It was revealed from the results that organisations intended to increase AI adoption over the next three to five years.

To address Research question two, the technology, organisation and environment factors of the TOE framework were examined to determine the factors influencing AI adoption. A research model was developed with eight hypotheses (page 30) and the variables operationalized to generate a survey. The results from the survey were used to test the model. The data from the survey were assessed for convergent and discriminant validity with use of principal component analysis. Thereafter, Cronbach's alpha was used to measure reliability and internal consistency. Pearson and Spearman correlation, multiple regression and stepwise regression analysis was performed to test the hypotheses. The results evidenced that data availability and top management support significantly influenced the adoption of AI. The other variables of perceived technology benefits, IT infrastructure, resource capability, and normative pressure were significantly related to AI adoption, while financial resources and competitive pressure were rejected as determinants of adoption.

7.2 Implications for Academia

This study has made at least three contributions to academic research.

First, through a systematic literature review and input from pre-test experts, the study has contributed a suite of AI technologies that can be considered in future research studies. Moreover, the current state of adoption was described using S-curves, supporting general theories of how technologies tend to diffuse.

Second, there are limited studies on artificial intelligence using the TOE framework and the quantitative methodology at an organisational level. Artificial intelligence research is still a field that requires a substantial amount of research. This study has contributed to academia through its development of a theoretical framework underpinned by TOE that can be used to explain adoption of AI technologies in organisations.

Third, there are a few studies using the TOE framework to study AI adoption in South African organisations. This study has made a contextual contribution to academic research by considering AI adoption in a developing country context. The sample included firms from a wide range of industries, but results are particularly relevant to the South African technology and financial services sectors.

7.3 Implications for Practice

The research study provides many insights into AI adoption for organisations. The results provide insight for various industries on the current state of AI adoption and organisations can thus benchmark themselves against their peers to measure where they are in their adoption journey. Results also show plans organisations have and the likely future state of adoption for the suite of AI technologies considered in this study.

Top management support was found to be a significant factor influencing AI adoption. Organisations should invest in their senior management by making them aware of the perceived benefits and implications of AI in the organisation. Arrangement of workshops that depict real world examples with AI experts should also be considered. Top management should also consider developing a strategic roadmap that encompasses an AI adoption strategy.

Data availability was also found to be a significant factor in AI adoption. A clear and concise data strategy is recommended to be carried out by organisations intending to adopt AI. Organisations should consider integrating data from various sources and systems to reside in a central repository. Securing data is also vital and adhering to data regulations and policies become necessary with adoption of AI. Data quality and monitoring mechanisms should be performed regularly to detect and manage any discrepancies. Lastly organisations should invest in data training for all employees to have a basic understanding of data principles, data quality and interpretation of data.

Factors such as financial resources and competitive pressure were not supported. This suggests organisations should focus more on assessing long -term perceived benefits than costs, but also on organisational readiness and industry norms when making decisions on new technology adoption, such as AI.

7.4 Limitations

The study was subject to certain limitations.

External validity states how results of a specific study can be generalised to other applicable studies (Bhattacherjee, 2012). The non-probability sampling approach that was used in the study poses a risk to external validity as the outcomes of the research may not be generalizable across other organisations not studied. Additionally, results may not be generalizable to other countries due to the unique developmental and economic context influencing technology innovation of South African organisations.

The study was cross-sectional in nature, the noted limitation is that the study will not provide an understanding for how the relationships of the variables will shift over time. Future researchers can explore a longitudinal study. In this study, underlying assumptions about causality can be developed only with reference to academic theory and literature.

The concentration of the research is on AI adoption decisions by South African organisations and not on AI technology implementation experiences of organisations, or the extent of actual benefit realisation.

Respondent bias was a potential possibility as the data was self-reported, an example would be social desirability bias such as where respondents may be prone to exaggerate their extent of AI adoption. Another potential bias as the study is cross-sectional is that participants are selected at a specific point in time and certain groups may be overrepresented or underrepresented.

Lastly, the study had 57 responses from the various South African organisations, a higher volume of responses could have impacted the results and relative significance of the TOE factors.

7.5 Future Research

The focus of this research study was to understand the factors that influenced AI adoption in organisations using the TOE framework. Future researchers can implement a longitudinal study to track the progress and impact of AI adoption over a time period. This will allow researchers to gain insight into the long-term effects of AI adoption on efficiency, productivity, and customer satisfaction.

Future studies can consider using other TOE variables such as organisation size, organisational culture, and complexity of technology to determine if these variables influence adoption decisions.

An interdisciplinary research study can also be considered where the complexities of the organisational, technological, and human factors can be studied. A collaboration between information systems, psychology, commerce, and organisations can be considered. This could lead to a more detailed understanding of the opportunities and challenges related to AI adoption.

In addition, collaborative studies between academic and industry researchers into successful and unsuccessful cases of AI adoption should also be considered. This can provide real-world examples and case studies to address the practical needs of organisations.

An opportunity exists for future researchers to explore large language models such as ChatGPT, BERT, RoBERTa and others. The use cases of these tools, integration, and deployment can be studied. This includes analysing the technical considerations such as infrastructure, scalability, and security policies to ensure seamless integration and adoption with existing infrastructure. Organisations are already using large language models for quality assurance (manufacturing), personalised shopping (retail) and risk assessments (finance). Other potential use cases where language models can be applied within organisations to solve current challenges or enhance benefits should be identified.

Lastly, AI policy and regulation research can be conducted to provide insight into the societal, economic, and legal implications of AI adoption. This will help shape regulatory frameworks that promote responsible and ethical AI adoption.

7.6 Conclusion

This study identified a suite of AI technologies relevant to South African organisations.
The study also closed a gap in current literature by contributing to the study of AI adoption using the TOE framework. The study showed the technological factor (data availability) and organisational factor (top management support) were most significant to AI adoption.

Organisations are now better able to determine on which AI technologies to focus and which practical steps to take to advance AI adoption.

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Appendix A: Summary of Pretest Survey

Pretest Question No.	**Pretest Question**	**Participant Responses**
1	What is the key deciding factors associated with new technology adoption such as Artificial Intelligence in your organisation?	• Cost and wider industry adoption • Adaptation of the employees to understanding the capabilities of AI and the benefits it brings to their daily tasks/job. • Doing things faster, with less resources • AI Use Cases
2	What are some of the benefits that your organisation has experienced from AI adoption?	• Reduced processing times • It leads to higher efficiencies due to the more stable operation capabilities it offers and thus leads to higher-quality product development. • Have more control over decision making. • Streamlining of the process
3	Is your organisation using AI technology?	• Yes: 75% • No: 25%
4	If you answered yes to the above question, please state the AI technology(s) used in your organisation	• Machine learning for OCR • Expert Systems • As a fintech company implementation is at various levels namely speech recognition, machine learning, virtual assistants etc.
5	The types of AI technology specified in my research paper are Speech Recognition Chatbots Image Recognition Robotics Process Automation Machine Learning Please specify if the above technologies are applicable to your organisation	• Yes: 75% • No: 25%

Table A. 1: Summary of pre-test Results

Appendix B: Summary of The Pilot Test Results

Question No.	Pilot Question	Participant Responses
1	Are the questions simple to understand? If not, please specify the questions that need improvement.	• Yes: 100% • No: 0%
2	Is the survey an appropriate length or is it too long? Please state the time taken to finish the survey.	• Good – 12 min • Happy –15 min • N/A • Good length – 15 min • Happy with the length – 15 min
3	In your opinion, were there any questions that were applicable to the study that was left out?	• Yes: 0% • No: 100%

Table A. 2: Summary of Pilot test results

Appendix C: Web Survey

SECTION A: Demographic Data

Please answer the following questions about yourself and your business area

Please specify your job title

Please state the duration that you have been with your current organisation?

- 0 - 1 year
- 2 - 4 years
- 5 - 7 years
- 8 - 10 years
- 10 years +

Please state how long you have been in your current job role?

- 0 - 1 year
- 2 - 4 years
- 5 - 7 years
- 8 - 10 years
- 10 years +

Please specify your organisation's industry sector

- Technology
- Retail Industry
- Basic Materials
- Oil & Gas
- Mining
- Financial Instituition
- Industrial
- Telecommunication
- Other

Please indicate if you are involved in Information Technology decisions for your business area

- Yes
- No

SECTION B: Technology Factors

Please specify which of the following Artificial Intelligence technologies have been implemented in your business area

	Yes, already adopted	Not yet adopted, but we have plans to adopt within the next 1-3 years	Not yet adopted, but we have plans to adopt within the next 3-5 years	No plans to adopt	Unsure
Machine Learning (use algorithms to improve experience by using data)	○	○	○	○	○
Natural Language Processing (Applying techniques to analyse text and speech in the human context)	○	○	○	○	○
Neural Networks(Neural networks are a form of computational simulation. The various layers of neurons process and transmit information)	○	○	○	○	○
Robotics Process Automation (Software technology used to build robots that mimic human actions)	○	○	○	○	○
Chat Bots/Virtual Assistants (simulates and analyses human conversation)	○	○	○	○	○
Image Recognition(Use of an application to recognise objects, people or places in images)	○	○	○	○	○
Speech Recognition (Converts human speech into written text)	○	○	○	○	○

Please state year technology was adopted first adopted

Machine Learning	
Neural Network	
Image Recognition	
Robotic Process Automation	
Chatbots/Virtual Assistants	
Natural Language Processing	
Speech Recognition	

Please rate the following statements by selecting the most appropriate option for your business unit:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
9. My business area is satisfied with our current level of adoption	○	○	○	○	○	○	○
10. My business area invests adequately in artificial intelligence technology	○	○	○	○	○	○	○
11. My business area has a strategy in place to guide AI adoption	○	○	○	○	○	○	○

Perceived Technology Benefit

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
12. AI can reduce operational costs in my business unit	○	○	○	○	○	○	○
13. AI is important to improve process efficiency in my business unit	○	○	○	○	○	○	○
14. AI is vital to reach new customers for my business unit	○	○	○	○	○	○	○

IT Infrastructure

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
15. AI will be compatible with supplier or customer software	○	○	○	○	○	○	○
16. My business area infrastructure can support AI technology	○	○	○	○	○	○	○
17. The development of AI technology is compatible with my organisation's legacy systems	○	○	○	○	○	○	○

Data Availability

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
18. My business area has access to data required for AI	○	○	○	○	○	○	○
19. Data supplied from my business unit is of good quality (complete, accurate)	○	○	○	○	○	○	○
20. My organisation has a data repository to store and process large amounts of data at an acceptable speed	○	○	○	○	○	○	○

SECTION C: Organisation Factors

Top Management Support

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat agree	Agree	Strongly Agree
21. Investment in AI technology is supported by top management in my business area	○	○	○	○	○	○	○
22. AI technology is considered by top management in my business area to offer a competitive advantage	○	○	○	○	○	○	○
23. AI is deemed strategically important by top management in my business area	○	○	○	○	○	○	○

Financial Cost

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat agree	Agree	Strongly Agree
24.High setup costs are associated with AI technologies	○	○	○	○	○	○	○
25. High maintenance costs are associated with AI technologies	○	○	○	○	○	○	○
26. AI adoption comes with resource training costs	○	○	○	○	○	○	○

Resource Capability

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat agree	Agree	Strongly Agree
27. Regular training occurs in my business area to ensure employees are acquainted with AI technologies	○	○	○	○	○	○	○
28. My business area encompasses a high level of AI associated knowledge	○	○	○	○	○	○	○
29. The rate of hire for highly skilled AI employees is regular in my business area	○	○	○	○	○	○	○

SECTION D: Environment Factors

Competitive Pressure

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
30. A high percentage of my organization's direct competitors use AI technology	○	○	○	○	○	○	○
31. Our direct competitors that have adopted AI are seen favourably by customers in the market	○	○	○	○	○	○	○
32. Our direct competitors that have adopted AI are seen favourably by their suppliers in the market	○	○	○	○	○	○	○
33. Our direct competitors that have adopted AI are seeing great benefits	○	○	○	○	○	○	○

Normative Pressure

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
34. Our customers have adopted AI extensively							
35. Our suppliers have adopted AI extensively							
36. AI adoption is a norm for our industry							
37. Trade and industry bodies relevant to our organization promote the use of AI							

Appendix D: Ethics Clearance Certificate

UNIVERSITY OF THE
WITWATERSRAND,
JOHANNESBURG

SCHOOL OF BUSINESS SCIENCES ETHICS COMMITTEE
CONSTITUTED UNDER THE UNIVERSITY HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)

CLEARANCE CERTIFICATE	**PROTOCOL NUMBER: CBUSE2062**
PROJECT TITLE	Factors Influencing Artificial Intelligence Adoption in South African Organisations: A TOE Framework
INVESTIGATOR	Kaneez Fathima Hoosen
SCHOOL/DEPARTMENT OF INVESTIGATOR	School of Business Sciences
DATE CONSIDERED	17 April 2023
DECISION OF THE COMMITTEE	Approved unconditionally
RISK LEVEL	Minimal Risk
EXPIRY DATE	31 December 2026

ISSUE DATE OF CERTIFICATE 24 April 2023 **CHAIRPERSON** ______________________
(Neetu Ramsaroop)

cc: Supervisor: Prof Jason Cohen

DECLARATION OF INVESTIGATOR

To be completed in duplicate and **ONE COPY** returned to the Chairperson of the School/Department ethics committee.

I/we fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure be contemplated from the research procedure as approved, I/we undertake to submit an amendment of the protocol to the Committee.

______________ 24 / 04 / 2023

Signature **Date**

Appendix E: Multiple Regression (Assumptions)

Technology Variables

Model		Collinearity statistics	
		Tolerance	VIF
1	(Constant)		
	Perceived Technology Benefit	0.716	1.396
	IT Infrastructure	0.501	1.995
	Data Availability	0.620	1.613
a. Dependent Variable: AI Technology Adoption			

We are satisfied with the collinearity as the tolerance values are close to 1, and the VIFs are below 5

Table E. 1 : Summary of Tolerance and VIF Multiple Regression (Technology)

The residuals are approximately normally distributed.

The scatter plot does not depict an obvious pattern, suggesting no violations of constant error variance

The histogram depicts residuals are approximately normally distributed.

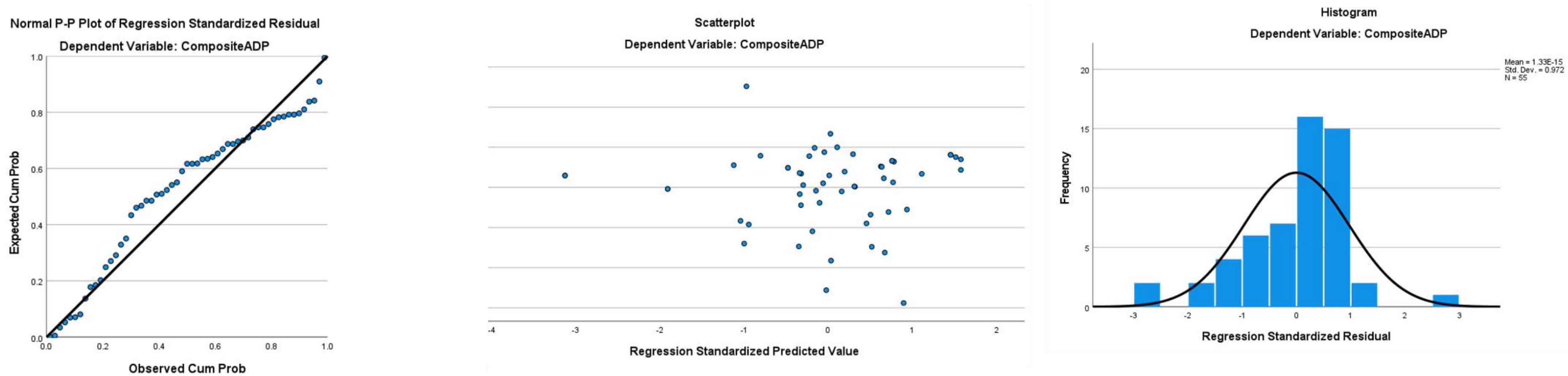

Figure E. 1: Residual P-Plot, Homoscedasticity, Histogram for Technology Variables

Organisational Variables:

Model		Collinearity statistics	
		Tolerance	VIF
1	(Constant)		
	Top Management Support	0.463	2.160
	Financial Resources	0.984	1.016
	Resource Capability	0.467	2.143
a. Dependent Variable: AI Technology Adoption			

We are satisfied with the collinearity as the tolerance values are close to 1, and the VIFs are below 5

Table E. 2 : Summary of Tolerance and VIF Multiple Regression (Organisation)

The residuals are approximately normally distributed.

The scatter plot does not depict an obvious pattern, suggesting no violations of constant error variance

The histogram depicts residuals are approximately normally distributed.

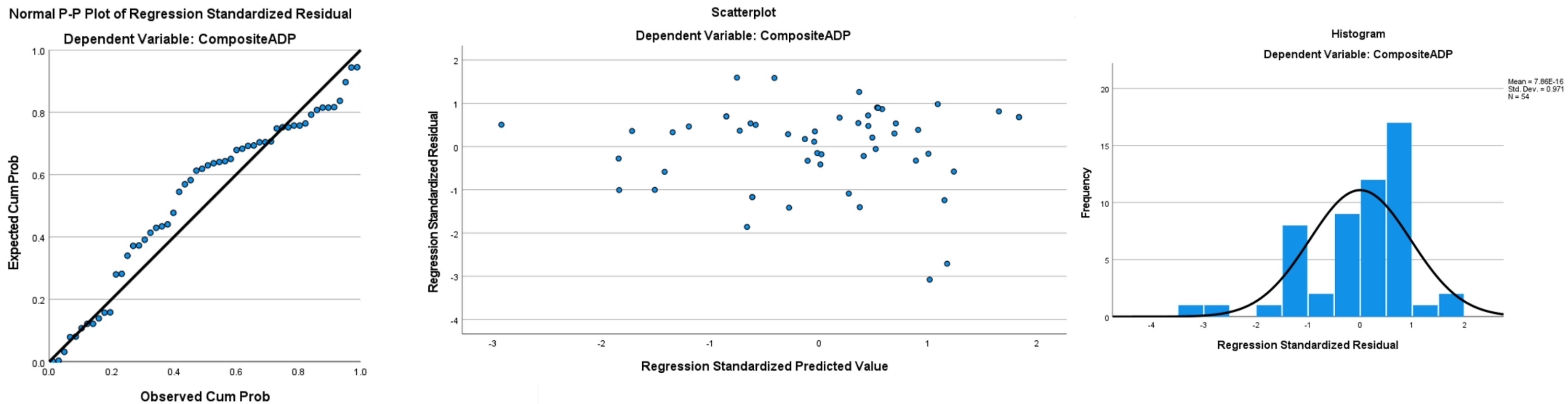

Figure E. 2: Residual P-Plot, Homoscedasticity, Histogram for Organisational Variables

Environmental Variables:

Model		Collinearity statistics	
		Tolerance	VIF
1	(Constant)		
	Competitive Pressure	0.578	1.729
	Normative Pressure	0.578	1.729
a. Dependent Variable: AI Technology Adoption			

We are satisfied with the collinearity as the tolerance values are close to 1, and the VIFs are below 5

Table E. 3: Summary of Tolerance and VIF Multiple Regression (Organisation)

The residuals are approximately normally distributed.

The scatter plot does not depict an obvious pattern, suggesting no violations of constant error variance

The histogram depicts residuals are approximately normally distributed.

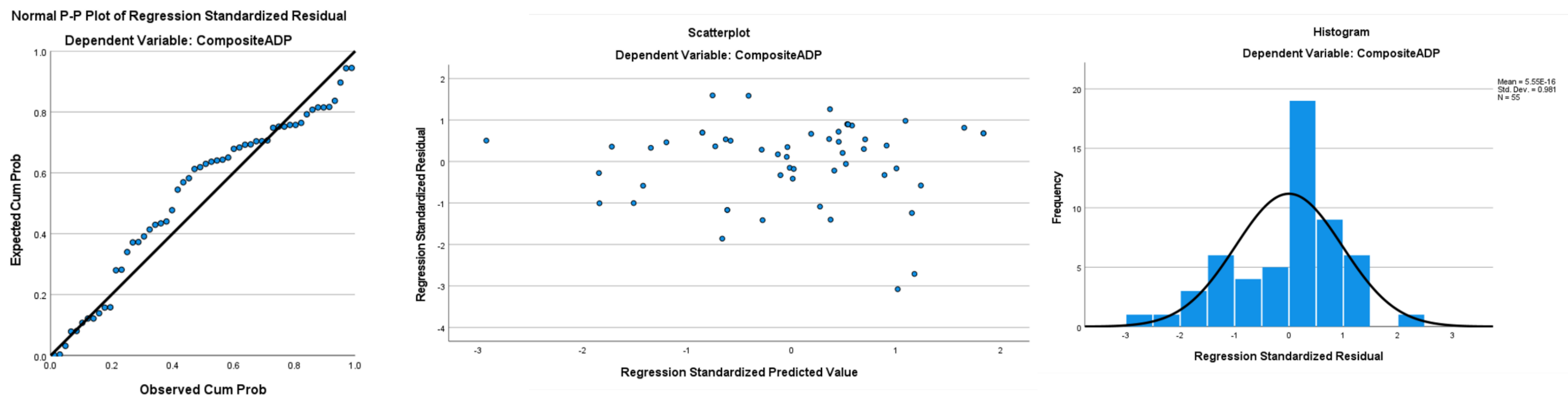

Figure E. 3: Residual P-Plot, Homoscedasticity, Histogram for Environmental Variables

Stepwise Regression

Model		Collinearity statistics	
		Tolerance	VIF
1	(Constant)		
	Perceived Technology Benefit	0.897	1.115
	IT Infrastructure	0.640	1.563
	Data Availability	0.815	1.227
	Top Management Support	0.815	1.227
	Financial Resources	0.999	1.001
	Resource Capability	0.787	1.271
	Competitive Pressure	0.999	1.001
	Normative Pressure	0.934	1.071
a. Dependent Variable: AI Technology Adoption			

Table E. 4: Summary of Tolerance and VIF Stepwise Regression

We are satisfied with the collinearity as the tolerance values are close to 1, and the VIFs are below 5

The residuals are approximately normally distributed.

The scatter plot does not depict an obvious pattern, suggesting no violations of constant error variance

The histogram depicts residuals are approximately normally distributed.

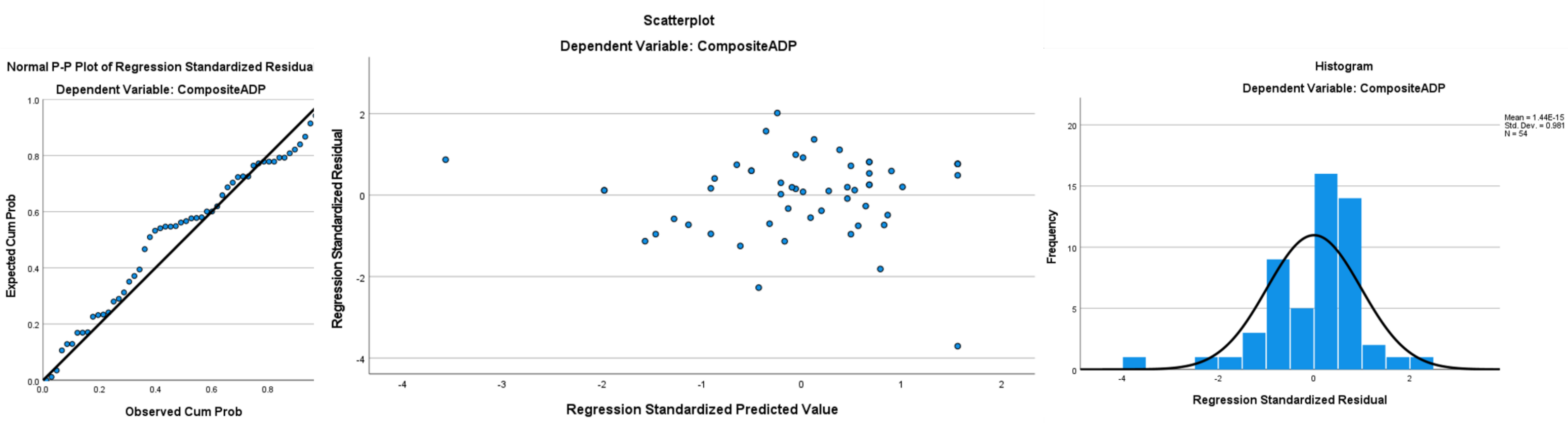

Figure E. 4: Residual P-Plot, Homoscedasticity, Histogram for Stepwise regression