The adoption of Intelligent Applications by South African Organisations

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

Johannesburg

23 June 2025

ABSTRACT

Digital disruption has impacted many industries globally. Not all industries have been equally impacted; some have experienced more disruption than others. The ICT industry, among others, is closest to the centre of the vortex indicating the extent to which it has been disrupted compared to others. Digital technologies are merging to leverage their combined capabilities in forming more powerful tools to aid industries to cope with organisational transformation.

This quantitative study uses the extended Unified Theory of Acceptance and Use of Technology (UTAUT) model to examine the relationship between the UTAUT constructs and the behavioural intention of employees to adopt intelligent applications in a South African ICT organisation. The model was extended to include General Awareness, Attitude and Trust, job classification, employment contract type, and education level as moderating variables to examine the influence on behavioural intention. The cross-sectional study included the collection of empirical data through an anonymous online survey. Respondents were also given the opportunity to respond to open-ended questions (divergent question technique) on barriers and enablers to new technology adoption.

The analysis results revealed that performance expectancy and effort expectancy are not significant predictors of adoption. Social influence is a weak predictor of adoption. General Awareness, Attitude and Trust, and facilitating conditions were strong predictors of the behavioural intention to adopt intelligent applications. Key outcome topics are insufficient training, management support and strategy, financial constraints, and data management. The results of this study contribute to the body of knowledge on extended factors of UTAUT on influencing the adoption of intelligent applications in the ICT Sector. The study also provides insights to ICT leaders, talent managers, and technology service providers on factors that support the adoption of intelligent applications.

Keywords: Adoption, Intelligent Applications, Artificial Intelligence, Disruption, Transformation, Unified Theory of Acceptance and Use of Technology, UTAUT, ICT, South Africa

DECLARATION

I, Chiresh Kawal, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination or any other university program.

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Date: 23 June 2025

ACKNOWLEDGEMENTS

Many people I have encountered in my life contributed to this journey in different ways.

I want to thank my parents who imparted to me the importance of education and perseverance. These characteristics formed the foundation to taking this path and completing the journey.

A special thanks to my sister and family for the care, love and support during the past years completing my studies.

To my friends, I am grateful for having all of you in my life. Thank you for setting the bar and providing guidance, for allowing me the space I needed on this journey of self-discovery.

To my management team, for starting me on this path and helping me accumulate the experience needed to grow in this field of study.

To my supervisor, Dr Tebogo Sethibe, thank you for the guidance and support during this process.

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LIST OF ACRONYMS

Abbreviation	Description
4IR	Fourth Industrial Revolution
AI	Artificial Intelligence
AIDUA	Artificially Intelligent Device Use Acceptance
AST	Adaptive Structuration Theory
AWS	Amazon Web Services
COVID	Coronavirus
CSV	Comma Separated Values
ERP	Enterprise Resource Planning
IBM	International Business Machines
ICT	Information and Communications Technology
IT	Information Technology
LIS	Library and Information Science
LSP	Logistics service providers
NPS	Net Promoter Score
POC	Proof of concept
RPA	Robotic Process Automation
SOE	State Owned Enterprise
Jamovi	Open-source Statistical Analysis Software for Social Science.
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
US	United States
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2

CHAPTER 1: INTRODUCTION

1.1 PURPOSE OF STUDY

Intelligent applications are defined as systems that possess embedded AI capabilities such as natural language processing, machine learning, predictive modelling, and adaptive automation. These applications differ from traditional software by their ability to learn from data, enhance user interactions, and evolve with organisational needs (Gartner, 2024; Cunningham, 2024). Examples include virtual assistants, AI-enhanced CRM systems, automated workflow engines, and predictive analytics platforms.

The purpose of this study is to examine the behavioural factors that influence employees' intention to adopt intelligent applications within a South African ICT organisation. The study applies an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework to assess how constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions—alongside moderating factors such as awareness, trust, attitude, and demographic characteristics—influence adoption behaviour.

While the research is situated within a single ICT organisation, this organisation serves as a methodological case due to its advanced digital capabilities, national footprint, and relevance to broader trends in South Africa's technology ecosystem. The intention is not to generalise statistically to all South African organisations, but to derive theoretically grounded insights that can inform future research and practice across similar ICT contexts. The single ICT organisation is referred to as Telecom X throughout this study for purposes of anonymity.

1.2 CONTEXT OF STUDY

In the face of volatile markets, it has become imperative for organisations to stay relevant and competitive. As industries continue to digitalise operations, there is a growing need to defend markets, safeguard revenues, and optimise operational efficiencies by adopting digital technologies through digital transformation initiatives.

The business landscape is rapidly evolving to meet existing customer demands and attracting new customers through highly competitive value propositions. The digital transformation wave of change has been accelerated since the occurrence of the COVID-19 pandemic Kim, (2020). Organisations globally have increased the rate of digital technology adoption. This study investigates the changes in consumer behaviour patterns after the pandemic. The study also examines the impact of the pandemic on business operations. Populations worldwide were compelled to make more use of digital technologies to accomplish their day-to-day tasks and accomplish their needs during the pandemic lockdown. The use of digital tools continued after the lockdown period giving rise to a ‘new normal’. This includes the increased adoption of digital messaging tools such as social media. Other tools include various video calling platforms, such as WhatsApp, YouTube and Twitter (currently called X) to keep in touch with friends and family in different locations. Using digital applications became common practice in maintaining social and professional relationships. Organisations began investing in digital tools (i.e. Microsoft Teams and Zoom) to maintain productivity levels. A sudden growth in the use of online meeting services such as Google Meet and Google Cloud video conferencing of over 60% day-to-day was reported Hardy, (2020). These drove efforts in introducing online platforms as new channels to provide customers with access to products and services that were traditionally only available through “brick and mortar” channels. These efforts took hold and presented several opportunities to grow revenues through investments in the implementation of various technologies to support business operations.

In the South African context, digital transformation efforts have already begun to gain momentum fast tracked by the COVID-19 pandemic. The adoption of digital technology tools has provided opportunities for organisations to implement hybrid operating models by servicing customers through traditional channels (i.e. brick and mortar) and digital channels alike. The effect of digital transformation is not isolated to organisations but has changed consumer behaviour and resulted in the increased use of online channels Kim, (2020). This adds pressure on organisations to adopt digital technologies to support online channels. The advancements in digital technologies have increased the use of digital applications in an organisation to ensure the best possible digital customer experience, which is fast becoming a major contributor to revenue and is directly proportional to customer satisfaction. This means the better the customer experience while a digital channel, the higher the customer preference to do business with a chosen organisation.

To enable this, organisations incorporated an array of technologies into existing business processes, such as systems using robotic process automation (RPA) and artificial intelligence (AI), to support new business models. Since inception, these technologies have evolved and have since been incorporated into the business operation and is used to support digital systems. Presently, digital technologies are widely used to service customer needs, which is constantly changing. Employees that use legacy systems often fail to meet the changing needs of customers. Having systems that support constantly changing customer needs through the frequent analysis of interconnected sources could provide organisations with the competitive advantage needed in the current climate. In the article, “The Role of Big Data for Marketing Opportunities in the South African Telecoms Market” Koeleh, (2021), the author investigates leveraging big data to create marketing opportunities in the South African market. Organisations in South Africa can leverage advancing digital technologies, like intelligent applications, to improve customer experience in volatile markets.

1.3 RESEARCH PROBLEM

In the paper, “Robotic Process Automation,” Van der Aalst et al. (2018) highlight the value of using RPA technology to improve the efficiency of organisational repetitive processes. The study also suggests using the AI technology in synergy with RPA to widen the scope of implementation by including more unconventional use cases. The Gartner findings at the time indicated that RPA on the Gartner Hype-Cycle was positioned at the “peak of inflated expectation”, meaning that this technology was in its infancy and was being offered by many vendors as a service to potential businesses, but the scenarios where this technology could be applied were limited.

Since 2018, digital technology has made significant advancements and, in the Gartner publication, “Emerging Tech Impact Radar: 2024”, the authors Nguyen & Casey, (2024) predict the growth in demand for intelligent applications over the coming years. Intelligent applications are essentially the merging of several digital technologies powered by AI providing opportunities to organisations struggling to deliver value from digital initiatives. Digital transformation globally has been greatly accelerated since the outbreak of the COVID-19 pandemic forcing organisations, employees, and customers to integrate digital applications into their daily professional and personals lives. The need for digital transformation for traditional businesses in South African is now at the top of the agenda. Traditional business processes need to transform to support new digital channels. The adoption of intelligent applications can ease the transformation process and provide new insights on the nature of customer behaviour, customer experience and market behaviour.

This study is aimed at contributing to the existing body of knowledge on technology adoption in organisations, specifically examining the adoption of intelligent applications in a South African organisation in the ICT sector. The study is refined further by examining this phenomenon at a management and non-management level of the organisation focusing on the customer support business function.

1.4 RESEARCH OBJECTIVES

The context of this research is focused on Telecom X. Using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model (Marikyan & Papagiannidis, 2023) the objectives are the following:

- **Research Objective 1:** To identify the extent to which the constructs of the extended UTAUT model (i.e. general awareness, attitude and trust, performance expectancy, effort expectancy, social factors, facilitating conditions) influence the intention to adopt intelligent applications in Telecom X.
  - **H1:** the hypothesis claims that the following constructs of the extended UTAUT model has a significant and positive impact on the behavioural intent to adopt intelligent applications.
    - **H1a:** Effort expectancy.
    - **H1b:** Performance expectancy.
    - **H1c:** Facilitating conditions.
    - **H1d:** Social influence.
    - **H2e:** General awareness, attitude and trust.

- **Research Objective 2:** To determine how the factors mentioned in objective 1 are influenced by demographics (i.e., age, gender, experience, level of education, job classification and employment contract) affect employee intention to adopt the use of intelligent applications in performing their business functions.
  - **H2:** The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by age.

- **H2a:** The relationship between behavioural intention and the **performance expectancy** is significantly influenced by **age**.
- **H2b**: The relationship between behavioural intention and the **effort expectancy** is significantly influenced by **age**.
- **H2c:** The relationship between behavioural intention and the **social influence** is significantly influenced by **age**.
- **H2d:** The relationship between behavioural intention and the **facilitating conditions** is significantly influenced by **age**.
- **H2e:** The relationship between behavioural intention and the **general awareness, attitude and trust** is significantly influenced by **age**.

- **H3:** The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by gender.
  - **H3a:** The relationship between behavioural intention and the **performance expectancy** is significantly influenced by **gender**.
  - **H3b:** The relationship between behavioural intention and the **effort expectancy** is significantly influenced by **gender**.
  - **H3c:** The relationship between behavioural intention and the **social influence** is significantly influenced by **gender**.
  - **H3d:** The relationship between behavioural intention and the **Facilitating condition** is significantly influenced by **gender**.
  - **H3e:** The relationship between behavioural intention and the **general awareness, attitude and trust** is significantly influenced by **gender**.

- **H4:** The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by the level of education.
  - **H4a:** The relationship between behavioural intention and the **performance expectancy** is significantly influenced by the **level of education**.
  - **H4b:** The relationship between behavioural intention and the **effort expectancy** is significantly influenced by the **level of education**.

- **H4c:** The relationship between behavioural intention and the **social influence** is significantly influenced by the **level of education**.
- **H4d:** The relationship between behavioural intention and the **facilitating condition** is significantly influenced by the **level of education**.
- **H4e:** The relationship between behavioural intention and the **general awareness, attitude and trust** is significantly influenced by the **level of education**.

- **H5:** The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by job classification.
  - **H5a:** The relationship between behavioural intention and the **performance expectancy** is significantly influenced by **job classification**.
  - **H5b:** The relationship between behavioural intention and the **effort expectancy** is significantly influenced by **job classification**.
  - **H5c:** The relationship between behavioural intention and the **social influence** is significantly influenced by **job classification**.
  - **H5d:** The relationship between behavioural intention and the **facilitating condition** is significantly influenced by **job classification**.
  - **H5e:** The relationship between behavioural intention and the **general awareness, attitude and trust** is significantly influenced by **job classification**.

- **H6:** The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by the employment contract type.
  - **H6a:** The relationship between behavioural intention and the **performance expectancy** is significantly influenced by the **employment contract type**.

        - **H6b:** The relationship between behavioural intention and the **effort expectancy** is significantly influenced by the **employment contract type**.
        - **H6c:** The relationship between behavioural intention and the **social influence** is significantly influenced by the **employment contract type**.
        - **H6d:** The relationship between behavioural intention and the **facilitating condition** is significantly influenced by the **employment contract type**.
        - **H6e:** The relationship between behavioural intention and **general awareness, attitude and trust** is significantly influenced by the **employment contract type**.

    - **H7:** The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by the amount of work experience.
        - **H7a:** The relationship between behavioural intention and the **performance expectancy** is significantly influenced by the amount of **work experience**.
        - **H7b:** The relationship between behavioural intention and the **effort expectancy** is significantly influenced by the amount of **work experience**.
        - **H7c:** The relationship between behavioural intention and the **social influence** is significantly influenced by the amount of **work experience**.
        - **H7d:** The relationship between behavioural intention and the **facilitating condition** is significantly influenced by the amount of **work experience**.
        - **H7e:** The relationship between behavioural intention and the **general awareness, attitude and trust** is significantly influenced by the amount of **work experience**.

- **Research Objective 3:** To uncover potential barriers for the use of intelligent applications by employees in Telecom X.

- **Research Objective 4:** To highlight potential enablers for the use of intelligent applications by employees of Telecom Xin performing their respective business functions.

1.5 SIGNIFICANCE OF STUDY

This study will contribute to the overall academic body of knowledge by providing insights into the evolution of digital technologies and the opportunities these technologies present to organisations in context of the 'new normal' (post-COVID-19) in South Africa. Many studies uncovered during the literature review reflect the widespread use of technologies although there is limited material on the opportunities presented through technological synergy. Customer and market behaviour have not settled since the pandemic, which presents fast changing opportunities and challenges, hence the focus on the adoption of new technologies and intelligent applications to keep pace with these changes.

Organisations choosing to adopt new technologies must consider effective change management practices to ensure success. The researcher is confident that the results will provide insights into the adoption of using "best fit" technologies to handle operational challenges.

1.6 DELIMITATION OF THE STUDY

The study presents a limited focus on the adoption of intelligent applications in an organisation in South Africa dealing with challenges presented by volatile markets.
The study focuses on one ICT organisation comprising multiple business units. Each business operates in a different market segment to the other business units. The study does not include other organisations in the ICT industry. The study also does not focus on specific 4IR technologies (i.e., RPA, AI, Big Data, etc) but rather on the combined use of selected 4IR technologies merged in a single intelligent application.

1.6.1 Definitions of Terms

Term	Definition

COVID-19	Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. Most people infected with the virus will experience mild to moderate respiratory illness and recover without requiring special treatment. (World Health Organisation, 2024)
Digital transformation	Digital transformation is the rewiring of an organisation, with the goal of creating value by continuously deploying tech at scale. McKinsey & Company, (2023)
Big Data	Big data refers to extremely large and diverse collections of structured, unstructured, and semi-structured data that continue to grow exponentially over time. These datasets are so huge and complex in volume, velocity, and variety, that traditional data management systems cannot store, process, and analyse them. (Google Cloud, 2024)
Artificial intelligence (AI)	AI refers to computer systems capable of performing complex tasks that historically only a human could do, such as reasoning, making decisions, or solving problems. (Coursera Staff, 2024)
Robotic Process Automation (RPA)	RPA uses intelligent automation technologies to perform repetitive office tasks of human workers. (IBM, 2024)
Customer service	Customer service is the support, assistance, and advice provided by a company to its customers both before and after they buy or use its products or services.

	(Grant, 2024)

1.6.2 Proposed Study Outline

ORIENTATION	
Chapter 1	Chapter 1 presents the introductory content under the following headings: • Purpose of the study • Context of the study • Research problem • Research objectives • Significance of the study • Delimitations of the study
LITERATURE REVIEW	
Chapter 2	Chapter 2 presents definitions from global forums and scholarly literature of the following: • RPA • AI • Intelligent applications The chapter also provides a summary of prior studies conducted for: • RPA • AI • Intelligent applications The chapter concludes with the following: • Analytical frameworks • Hypothesis development • Conclusion of literature review
RESEARCH METHODOLOGY	

Chapter 3	Chapter 3 presents the various components of the methodology considered for this study including: • Research approach • Research design • Population and sampling • Data collection methods and procedures • Validity and reliability • Research instrument • Data analysis • Limitations • Ethical considerations
KEY RESULTS AND FINDINGS	
Chapter 4	Chapter 4 presents the findings and analysis from the survey data and is detailed under the following broad headings: • Statistical Analysis • Text Analysis
DISCUSSIONS OF THE FINDINGS	

Chapter 5	Chapter 5 contains a discussion of the results and findings of this study including:
	• SUMMARY OF THE STUDY
	  o Research Objective 1
	  o Research Objective 2
	  o Research Objective 3
	  o Research Objective 4
	• CONCLUSION TO FINDINGS AND RESULTS

RECOMMENDATIONS, LIMITATIONS AND FUTURE RESEARCH	
Chapter 6	Chapter 6 draws recommendations, lists limitations of the study and suggests future research.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

The aim of this chapter is to review prior literature on artificial intelligence (AI), Robotic Process Automation (RPA), and intelligent applications to investigate the need for adopting intelligent applications in organisations in South Africa.

2.2 DEFINITIONS

2.2.1 Artificial Intelligence

This section focuses on the definition of AI and seeks to clarify what this technology is and what it means to society. There are numerous different definitions that could easily be confusing. The book *Digital Business* defines AI as a broad field essentially entailing computer algorithms that can learn and change Armstrong & Lee, (2021). The authors consider AI as one of the digital technology's great advancements and is part of the virtuous triangle concept that underpins the Fourth Industrial Revolution (4IR). The power behind AI lies in the use of specialised AI algorithms that enable computer systems to learn.

However, AI goes beyond the association with algorithms. Other definitions of AI states that it influences perception in one way or another. The European Commission proposed a definition that encompasses a broader perspective, namely that AI refers to systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals (European Commission, 2019). This definition is also referenced in the article, "Mission AI" Sheikh et al., Artificial Intelligence: Definition and Background, (2023), where the authors interrogate different parts of the definition drawing attention to "some degree of autonomy" as being vague.

Another AI definition variant stated in the paper, "A Scholarly Definition of Artificial Intelligence (AI): Advancing AI as a Conceptual Framework in Communication Research" by Gil de Zúñiga et al. (2023), is that it is the tangible real-world capability of non-human machines or artificial entities to perform, task solve, communicate, interact, and act logically as it occurs with biological humans. The study elaborates on this definition by drawing attention to dimensions such as the level of performance and the level of autonomy. The constant learning and changing nature of AI are most likely what make this technology difficult to define.

2.2.2 Robotic Process Automation

This section of the chapter focuses on the definition of RPA. Armstrong and Lee (2021) provided a definition for RPA as a software tool that mimics and replicates manual and repetitive human actions in software space to automatically fulfil a process or part of a process, with the ability to work with and between multiple programs and the ability to either include human intervention or to be completely automated. RPA is referred to as a foundational technology since it is a widely adopted technology. The technology provides the following benefits to organisations:

- Mimics human behaviour. If configured, RPA can mimic human behaviour for repetitive tasks and actions using software applications.
- Switches between applications. RPA can switch between multiple applications to complete activities of a process.
- Has dedicated credentials. RPA is regarded as a user with its own login credentials for various applications.
- Able to do autonomous process execution. RPA can execute the tasks of a business process with a consistent result. It also possesses the ability to halt process execution awaiting user input.
- Contains a decision engine. RPA can make decisions when executing business processes based on the outcomes of each task in the process.

Although RPA offers many benefits to an organisation, the technology is not without its challenges. The follow challenges apply to the adoption of RPA:

- Process risks. In mimicking human behaviour, the technology could lead to incorrect decision making.
- Ethical risks. In some scenarios RPA is viewed as a job displacement technology and holds the risk that it will replace people in the workplace.
- Security risks. Protection of sensitive and personal data collected or process by the systems using RPA are compromised.

2.2.3 Intelligence Applications

The authors of previous research articles hinted at the possibility of RPA technology becoming more intelligent to drive widespread adoption. Van der Aalst et al. (2018) suggested that integration of artificial intelligence techniques into RPA will enable the technology to support more complex tasks and decisions. Independently, both RPA and AI technologies have specific use cases within each sphere. The benefits and challenges are evident in the prior literature reviews section. With advancements in digital technologies the widespread adoption of technological synergies is becoming more apparent.

In an article by Kanakov and Prokhorov (2022) they state that, “RPA is dedicated to applying cutting-edge technologies, including artificial intelligence (AI) and machine learning, to increasingly automate processes and empower people” quoted from the abstract (Kanakov & Prokhorov, 2022). The authors explored the adoption of artificial intelligence techniques in the RPA to digital employees. RPA possesses the capabilities of mimicking user behaviour using application interfaces or direct integration with application programming interfaces (APIs). These capabilities are limited by what the users programme the technology to accomplish unless integrated with AI technology to provide more process flexibility and decision making.

In the article, “Robotic Process Automation and Artificial Intelligence in Industry 4.0 – A Literature review” (Ribeiro et al., 2021), the authors resonate the same sentiment as above. The aim of the study was to prove that AI techniques incorporated in RPA can improve organisational processes in the context of the 4IR. In the report by Van der Aalst et al (2018) and corroborated by the Gartner News Room (2018) the Gartner report at the time was quoted as saying, “RPA tools are at the ‘‘peak of inflated expectations’’ in the so-called Hype Cycle”. RPA is being offered by many vendors suggesting that RPA is new. In the Gartner article, “30 Emerging Technologies That Will Guide Your Business Decisions” (Nguyen & Casey, 2024), intelligence applications (synergy between RPA and AI) will reach an early majority (i.e., more than 16% target market adoption) in one to three years. This is intended to guide product owners in terms of technology adoption.

2.3 PRIOR STUDIES

2.3.1 Artificial Intelligence

This section focuses on prior studies regarding AI adoption in various organisations from 2020 to 2024. The ten studies in review are Wamba-Taguimdje et al. (2020), Malope et al. (2021), Koeleh (2021), Kelly et al. (2022), Hartzenberg (2022), Booyse and Scheepers (2023), Achmat, (2023), Subaveerapandiyan et al., (2023), Udo et al. (2024) and Hokonya (2024).

In the paper by Wamba-Taguimdje et al. (2020), the authors aimed to study the influence of AI on a firm's performance by examining the transformation projects that are AI-based. The study used the four-step sequential approach, namely (i) analysis of key concepts, (ii) exploration of industrial sector case studies, (iii) AI service provider data collection, and (iv) AI literature review. The method involved the review of 500 case studies from various websites, namely AWS, IBM, Universal Robots, Cloudera, Conversica, to name a few. The aim was to study the business value of these organisation's AI-enabled transformation projects. The findings from this paper show the potential of AI to optimise processes and improve on automation. The nature of the technology also presents the benefits of prediction, detection, and interaction with the users. The use of AI in organisations revealed other benefits, specifically at the macro level (organisational and departmental level) and at a micro level (process level). The study provides managers with insights into the advantages of using AI technology in the organisation to strengthen performance and increase competitive advantage.

In the paper by Malope et al. (2021), the authors examined the opportunities introduced to South African state-owned enterprises (SOEs) by 4IR technologies. South Africa is regarded as a developing economy, and the study investigated the value of SOEs and the South African government initiatives in leveraging the important components of the 4IR. The study regards Blockchain, Advanced Analytics, AI and IoT as some of the important components of 4IR. The method involved a literature review to analyse several propositions in combination with technology adoption frameworks (i.e., Technology-Organisation-Environment, Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology). A new framework for technology adoption and digitalisation for South African SOEs was compiled. The findings reveal that SOEs play a crucial role in the economy, especially in a developing economy like South Africa. This is confirmed by the literature review regarding the role of SOEs from a global perspective namely that embracing digital technology offers many benefits to the South African SOEs, notably the opportunities and challenges presented by the adoption of artificial intelligence in SOEs.

A research article by Koeleh (2021) investigates the role of big data for marketing opportunities in the South African telecoms market, with the focus on the mobile operators MTN and Vodacom. Although the South African market has four mobile network operators, MTN and Vodacom were selected for the study due to their dominant market position and network coverage in other countries. The study sought to understand how big data can be applied to better understand changes taking place in South Africa. The method for data collection was qualitative data (i.e., qualitative combined with primary and secondary data). Interviews were conducted with available staff of both organisations. Primary data in the form of official reports and secondary data in the form of existing research pertaining to the focus companies and South African market trends were used. The report findings reveal that big data can be applied to South African telecoms companies through predictive modelling of customer needs. Digital disruption is reducing the effectiveness of traditional marketing efforts. Since the COVID-19 pandemic, data-driven initiatives have spiked in adoption adding to the pool of data that provides insights to customer pain points, such as healthcare and education. Big data support telecoms companies in providing solutions or partnering with solution providers to service customers.

In the article by Kelly et al. (2022) a systematic literature review of five databases is presented. The predicted infiltration of AI technology in most industries fuelled the spike in research papers focusing on user acceptance. The research on the topic was found to be scattered and disorganised. The systematic literature review of the topic was conducted on fives databases using user acceptance and AI technologies as a filter criterion. The databases were EBSCO host, Embase, Inspec, Scopus, and Web of Science. The results of the search identified 7912 articles of which, 60 were used in the study. The Technology Acceptance Model (TAM) was most used. The TAM and UTAUT models were used with a high degree of success. The culture factor is an important element to consider when conducting research across demographics. The emerging AIDUA model (AI Device Use Acceptance) could provide more insight into the acceptance of AI technology in various industries and adds two outcome stages (willingness and rejection). Naturalistic observation is limited in the field of study and research should consider this method in future research to adequately assess the adoption of AI. This paper does contribute to the existing body of knowledge on the study of AI uptake.

In the research article by Hartzenberg (2022), the purpose of the research was focused on the influencing factors for adoption of new technologies in Vodacom mobile phone retail outlets. The study was limited to the retail outlets in the North-West province of South Africa. The aim was to identify challenges that stem from the innovative technology adoption. The challenges prevented the retail outlets from leveraging opportunities provided by digital technology. A qualitative research method was used to collect primary data for analysis and secondary data were sourced from other research papers. A total of ten interviews were conducted from randomly selected participants from various Vodacom retail outlets across the North-West province. The participants ranged from store owners to frontline staff. The study utilised the inductive research approach (i.e., observation, patterns, tentative hypothesis, theory). The findings revealed that there was consistency in the belief that technology improves the quality of people’s lives, improves business performance and increases operational efficiency. The study further revealed that the lack of knowledge about the technology and limited training on how to use the technology was a major negative contributor to adoption. The results also cited the rate of change of technology as another factor that slows adoption. The outlet management needs to focus more on the training and development to ensure successful adoption of the technology.

While AI has shown promise in assisting human decision making, there exist barriers to adopting AI for this purpose. In the research article by Booyse and Scheepers (2023) the aim of the research was to identify the barriers that prevent the organisation from using AI in decision making. This function was traditionally performed by knowledgeable and skilled workers, but AI technology can be used for making decisions and not only for performing automation tasks. A qualitative method using interviews with 13 senior managers in South Africa was conducted. The senior managers were selected from organisations involved with AI technology adoption. These individuals are familiar with the concept and should be in a better position to identify the barriers to AI inclusion in the decision-making process. The study applied the adaptive structuration theory (AST) model to AI decision making adoption. The following barriers to adoption were identified:

- human social dynamics – the need for employees to socially interact with one another.
- restrictive regulations – regulation that could potentially influence organisations into choosing to employ people rather than to adopt new technology.
- creative work environments – the ability for human beings to develop new knowledge from nothing whereas AI would need historic data to base its future decisions on.
- lack of trust and transparency – there is no clear way to rationalise the decisions made by AI and this leads to a lack trust in the adoption of the technology.
- dynamic business environments – fast changing business events could render AI ineffective since AI depends on historic data to learn, and this may not always be available.
- loss of power and control – strong change management practices are essential for AI adoption. This can only be accomplished through awareness campaigns and reskilling employees affected by AI to encourage buy-in.
- ethical considerations – this looks at the ability for AI to act ethically when faced with difficult decisions involving people.

In the paper by Achmat, (2023), the author argues that AI, though being around for many years, has grown substantially in the last ten years due to commercialisation and affordability of computing resources. Many organisations quickly adopted technologies like AI, while other organisations struggle to understand how assimilating AI in their organisation will yield any benefit. The purpose of the report is to fill the gap in understanding how AI can be used to drive organisational change. The initial step was to describe the features of AI and how these could be leveraged to drive change in the organisation. The identification of key affordances is made possible through affordance theory. This study adopts a qualitative interview method to collect data for analysis to theorise how AI technology features can drive organisational change from an AI practitioner's point of view. An interview guide was compiled, and all interviews were conducted online due to the COVID-19 pandemic.

The findings of the study identified eight affordances that are key to organisational change:

- Analysing risk – determines the organisation's exposure to risk.
- Analysing needs – involves understanding customer needs or operational needs.
- Forecasting – includes planning underpinned by insight.
- Assessing efficiency and effectiveness – involves assessing processes to determine optimisation regarding this affordance.
- Providing prediction criteria – supporting decision making by combining affordances to product insightful outcomes.
- Translating information – the AI activity of translating the information from sender to recipient.
- Tailoring information – process of customising information to suit the recipient.
- Improving predictability –involves capturing information accurately.

A research paper by Subaveerapandiyan et al. (2023) investigated the knowledge about and perception of AI among library and information science (LIS) professionals in Zambia. While librarians in Zambia have a positive outlook regarding artificial intelligence, they also expressed concerns about AI replacing the role of librarians. The paper also focuses on the barriers hindering the adoption of AI technologies in the Zambian context. The research paper suggests that libraries should take the findings of the report into account before implementing artificial intelligence solutions. The study used the collection of primary and secondary data to achieve the outcomes of the research report. The collection of primary data involved a structured survey distributed to 469 participants of which 245 responded. The survey used a 5-point Likert scale. The secondary data were sourced from books, websites, and published articles. The findings of the report show that the librarians and LIS professionals agree that AI is important for the effectiveness and efficiency of the library value. Respondents also agree that AI will make work easier and reduce disparities. The negative implication of AI adoption is that the technology will make LIS professionals lazy and threaten employment. There is strong agreement that upskilling, budget and the availability of service providers specialising in AI technology are required to remove adoption barriers.

In the paper by Udo et al. (2024), the authors compare the challenges, opportunities and adoption trends of information and communication technology and emerging technology trends between Africa and the United States. The aim was to identify key drivers for the adoption of technology. Disparities are shown in the outcome of the comparative analysis between the United States and Africa implying that cross-continental collaboration could potentially close the gap. Understanding and decreasing the gap between the continents through collaboration could lead to an increase in technology adoption and drive transformative change. The method of review used was primary data collection from research papers and secondary data collection from reports published by global organisations including the World Bank. Technology adoption in Africa lag the United States due to digital infrastructure, regulatory constraints, and lack of investment. The United States has supportive policies (i.e., research grants, tax concessions, favourable regulatory environment) to help with technology adoption. Socio-economic factors that present barriers in Africa include education quality, low income, digital access). Cultural and ethical factors in Africa include data privacy regulations, traditional beliefs and practices, data protection and cyber security.

This following paper aims to obtain insight into the use of artificial intelligence (AI) on customer experience in the Zimbabwean telecom companies. The study by Hokonya (2024) aimed to uncover the key themes, trends, and insights on the relationship between AI and customer experience. The study uses a qualitative research design employing semi-structured interviews targeting customers, employees, and management of ICT companies in Zimbabwe. The findings used a customer experience matrix to measure the outcomes of the study. The matrix included customer retention, churn rate, return on investment, net promoter score (NPS). All metrics showed a marked improvement in the implementation of AI technology. The use of AI platforms yielded positive sentiments from customers through easy access, ease of use, convenience, chatbots (neutral). Challenges for AI implementation included the necessary time to implement solutions, the complexity associated with AI technology, customer buy-in before technology implementation, and dynamic customer behaviour. Al of these have an impact on the complexity of implementation. Potential opportunities were the phased implementation of simple algorithms to drive customer journeys.

2.3.2 Robotic Process Automation

This section of the study focuses on prior studies regarding RPA adoption in various organisations from 2020 to 2024. The twelve papers in review are Cichosz et al. (2020), Nortje (2022), Qwabaza (2022), Sethibe and Naidoo (2022), Tsao et al. (2023), Norzelan et al. (2023), Farinha et al. (2023), Perdana et al. (2023), Achalan and Wickramarachchi (2024), Ayinla et al. (2024), Kanakov and Prokhorov, (2022), Ribeiro et al. (2021).

The rapid digital technology advancements in the logistics industry have changed the fundamental business practices of organisations. In the paper by Cichosz et al. (2020), incumbent logistics service providers (LSP) are compelled to digitalise to keep up with practices of this increasingly competitive landscape. Many LSPs struggle to digitally transform. This paper focused on identifying elements and best practices to digital transformation in LSPs and barriers to digital transformation. The method of analysis involved two phases. The first phase was a literature review to uncover potential barriers and successes of digital transformation efforts. The results were used as input in preparation for the interview protocol. The second phase involved data collection through interviews with industry experts. The findings revealed five barriers and eight success factors through leading practices. The main barriers identified are logistics network complexities and the shortage of resources. Leadership executing a digital transformation vision and creating a supportive culture are considered successes.

Traditionally, firms in South Africa had no need to include technology governance as part of their corporate governance or policies. As the use of technologies grows so too does the role they play in the policies, procedures, and governance of firms. Lack of consideration could potentially expose the firm to threats and vulnerabilities. In the paper by Nortje (2022), the author aimed to investigate which policies and principles should be incorporated in the governance principles of firms specifically when adopting RPA technologies. The study used the qualitative method and the theory of constructivism to formulate the knowledge required. Interpretivism approach through semi-structured interviews with industry experts to demystify the effects of RPA technologies. Seven governance principles are proposed by the author to assist South African firms with RPA governance, namely:

- Include the elements of digital governance in the corporate policy.
- Access management

- Adopt RPA in an ethical manner.
- Develop people and digital skills and reduce process risk.
- Implement cybersecurity principles and cybersecurity risk management.
- Provide data protection, data management and data security.
- Incorporate digital and 21st-century skills for users.
- Manage the impact of RPA on employees.

AI technologies are quickly becoming a catalyst for disruption in organisations. The technology assimilation into processes and contribution to decision making is transforming the way organisations operate and deliver value. In the paper by Qwabaza (2022) the author investigates the success factors for adopting AI by financial services companies in South Africa. The study focuses on understanding the factors affecting the adoption of AI in this industry. The method uses a combination of diffusion of innovation theory and technology-organisation-environment framework through an online survey mechanism. The target group comprised of employees in financial services companies in the South African context. The data analysis employed the use of structural equation modelling framework. The results of the study revealed that AI adoption is only influenced by technical capabilities and complexity. Managerial capabilities had an indirect impact on AI adoption. In conclusion, the cost of AI adoption, the time taken to innovate, identifying the use case for the application should be considered before adoption. Further, government involvement, pressure associated with competition, vendor/supplier partnerships, and factor external to the environment had significance for adoption. In addition, the study focused on the assimilation of the artificial intelligence technology by customers once the organisation had adopted AI using TAM. The results showed that perceived ease of use and perceived usefulness are key to customer experience of AI.

In the paper by Sethibe and Naidoo, (2022), the authors describe a study conducted in the auditing profession in South Africa. The auditing profession is often faced with high costs of manual activities and is subject to reputational damage from false results due to high dependency on manual tasks. The objective of the study was to determine the factors influencing the adoption and use of robotics in auditing activities. The study used the UTAUT and the quantitative approach by surveying 59 professional auditors and 26 non-auditors within the South African auditing profession.

The survey made use of questionnaires and semi-structured interview questions. The study concluded that the key factors influencing the use of robotics is performance expectancy and facilitating conditions. The critical barriers to robotics adoption in this profession were identified as poor data quality, lack of training and inadequate investment in robotics technology. The potential key enablers to adoption were technology skills, leadership support and adequate change management processes.

The use of RPA technology is said to target high repetitive rules-based processes in various contexts to increase the rate of events (scalable) with minimal errors. In the paper by Tsao et al. (2023), the authors proposed a demonstration (i.e., proof of concept (POC)) of the RPA technology by applying this technology to the operation of collecting and analysing data. The process also alerted the user of any errors in the data by removing the data from the process and thereby improving data quality. The conclusion from the proof of concept was that the technology met the requirements and provided a convenient, fast, and automated monitoring tool. The harmful particulates (i.e., erroneous data) in the data process triggered alerts to users via SMS (part of PoC). The study reported several benefits of implementing RPA technology in this scenario, namely RPA tools were easy and convenient to use. RPA overcame integration hurdles between systems of different suppliers. RPA showed usability and scalability during execution. It is worth noting that UiPath was the RPA software of choice for the POC. The study lists these potential barriers to the implementation of RPA technology, namely the cost of implementing the software and time to analyse and implement the robotic processes.

AI technology is fast evolving. The technology can be adapted to operations in different industries. In the research article by Norzelan et al. (2023) the authors studied the acceptance of AI technology among the heads of the accounting and finance sections of an organisation focusing on the shared services industry. The aim of the study was to determine what factors influence the acceptance of AI in this industry and specifically in the finance and accounting area. The study used the UTAUT and theory of planned behaviour (TPB). The method used online questionnaires made up of two parts (key questions and demographics). The results show that technical capability, skills, attitude, and performance expectancy are key when determining acceptance of AI. However, facilitating conditions, effort expectancy and social influence show no link to AI acceptance. From the results of the questionnaire, it is clear where organisations should focus their efforts specifically in finance and accounting discipline of the shared services industry. This study was conducted in Malaysia and contributes to the overall subject matter.

The performance of an organisation is largely determined by the efficiency in delivering the value proposition. In the research article by Farinha et al. (2023), the authors are familiar with the efficiency delivered by RPA and opted to examine the criteria that organisations should consider in deciding which processes to automate. The results of this study contribute to the body of knowledge on this topic since there is a lack of research in this area. The study conducted a systematic literature review on the topic and then conducted a Delphi study with professionals in RPA. The purpose of this approach was to fine-tune the insights gathered from the literature. The results show the main criteria organisations need to consider when identifying which process to apply RPA to. The finding identified 32 criteria from the literature review for consideration by organisations. Based on the opinions of experts the top five were feasibility, accurate process description, input and output data, application access and data security. The study resulted in the creation of a framework that organisations can use to determine which processes to automate. The framework can be evolved through more studies in the field and in different organisations.

Digital technologies are becoming more accessible to organisations as the advancements in various technologies gain momentum. Prototyping, a topic covered in Lean Startup, is fast becoming a method to test assumptions on technology benefits to a business (Armstrong and Lee, 2021). In the paper by Perdana et al. (2023), the authors examined auditing scenarios in four auditing firms. The aim was to improve task accuracy and efficiency by introducing the potential use of RPA technology. The study was conducted by prototyping the introduction of RPA technology into specific processes to prove the benefits of RPA in the identified practical business processes. The following scenarios were identified:

- Employee loan auditing: Vouching, adherence, and recalculation.
- Bank reconciliation
- Analytical procedures
- Three-way match
- Search for unrecorded liabilities.
- Audit of statutory records

For each scenario, the research team had advised the following to the organisation:

- Develop duration and strategy.
- Describe benefits and challenges of implementation.
- Provide as-is and to-be business process changes.
- Provide an analysis of how the technology will help the firm.
- Compile guidelines for RPA development in future.

Part of the feedback to the firm included the challenges and opportunities of implementing RPA on a broader scale.

An industry that lacks sufficient research involving the adoption of digital technologies as part of digital transformation is ICT. In the research article by Achalan and Wickramarachchi (2024), the authors investigated the impacts of RPA in the telecommunications industry in Sri Lanka. The researchers utilised a quantitative methodology, conducting an online survey with 114 industry professionals to explore RPA adoption drivers, challenges, and performance impacts. The study revealed that RPA adoption significantly improved operational efficiency, costs, customer experience, and workforce dynamics, explaining 63 to 91% of the variance. Notably, RPA demonstrated the ability to optimise operations, reduce expenses, enhance customer service, and provide workforce gains within the Sri Lankan telecom sector. These findings offer empirical evidence for organisations in Sri Lanka to formulate strategies leveraging RPA for competitive advantage in the rapidly evolving telecommunications landscape. The research further highlights the transformative potential of RPA in enhancing various aspects of telecom operations, emphasising the importance of informed decision making and strategic adoption in the telecommunications industry.

In the research article by Ayinla et al. (2024), the authors investigated the impact of RPA on modern accounting practices through a systematic literature review and content analysis. The researchers used specific keywords related to RPA and accounting, limited to English documents from 2013 to 2023. They selected literature based on the relevance to the study's aim, focusing on RPA's role in accounting, the benefits, challenges, and its integration with existing systems. The data analysis involved content analysis to identify key themes, patterns, and findings related to RPA in accounting. The study found that RPA in accounting automates routine tasks, enhances operational efficiency, and allows accountants to focus on strategic activities, leading to improved productivity and accuracy. A portion of the findings was attributed to the predicted enhancements of RPA involving the integration of AI technologies to enhance analytics and decision making. This route revealed challenges that required balanced management and governance policies to ensure the ethical use of this technological advancement. This research is crucial as it provides insights into the transformative impact of RPA on accounting practices, shaping the future of the profession.

In the research article by Kanakov and Prokhorov (2022), the authors explored the application of two separate technologies namely, AI and RPA. While the technologies have previously been dedicated to specific and limited use cases, the combination of these technologies provided a wider set of applications and has many combined benefits. The potential topic in this study moved from increased efficiency to empowering people. The example quoted in the study is recognising useful content in emails. For example, the RPA will send an email to a user and the AI will interpret the content and summarise the relevant points when received. The article also made mention of the concept of digital employees where the AI tasked RPA to perform certain activities. Several topics are covered in the research article, namely:

- Intelligent efficiency – digital employees for simulation and substitution.
- Analytics: process discovery and activity identification – new processes can be uncovered by AI based solutions.
- Text recognition – digital document management.
- Image recognition – comparative picture analysis, facial recognition application.
- Opportunities to improve customer service efficiency – combining RPA and AI for call analysis.

The technology evolution has resulted in the proliferation of information systems in society. Several services offered by institutions in society are now accessed through digital channels giving rise to digital services. In the paper by Ribeiro et al. (2021), the authors considered the 4IR technologies as change agents. Individually, each technology services a limited set of use cases. However, when these technologies work in concert with each other they yield much greater benefits. The aim of this research articles was to study the benefits of combining RPA and AI to improve business processes in organisations. The method was to source and analyse information on RPA tools to determine which tools incorporate a form of AI technology in support of and integration Enterprise Resource Planning (ERP) systems. A table showing the results of the comparison between the RPA product and the AI technology is provided in the research article. In conclusion, RPA technology in the context of 4IR contains, on a small scale, elements of AI algorithms and techniques when applied in various business scenarios. The combination of all these concepts and technologies introduced a significant change in industrial processes, impacting digital processes throughout the company.

2.3.3 Intelligent Applications

This section of the study focuses on prior studies on intelligent applications. The two papers in review are by Nguyen and Casey (2024), and Wiles (2023). The literature reviews for this topic are limited by the terminology used in the search criterion of Google Scholar. The technology, now termed, intelligent applications was given by Gartner in the article by Nguyen and Casey, (2024). Though prior studies may have been referring to this type of technology synergy, the researchers may not have referenced the technology according to the new name. The authors focused on guiding product leaders on the impact of emerging technologies and trends, helping them decide when to invest in these technologies for business success. The researchers used the Impact Radar to highlight the most impactful technologies for 2024, categorised under four key themes: the smart world, productivity revolution, privacy and transparency, and critical enablers. They found that generative AI is driving a productivity revolution by enhancing existing features and adding new functionality which has led to widespread adoption across enterprises. This is relevant because it provides insights for product leaders to strategically plan investments around disruptive technologies, differentiate customer experiences, and stay ahead in a rapidly evolving technological landscape. Another technology showing promise of increased adoption in organisations is intelligent applications. This technology is grouped along with other technologies in the category of ‘productivity revolution’ as this is seen as a technology that will enable employees to maintain or even improve their productivity.

In the article published by Gartner by Wiles (2023), the author describes what intelligent applications are and the value these applications have for a business. The article sites three characteristics of intelligent applications,

- **Intelligent decision making:** connects various data sources with analytics, drives continuous and contextual decisions.
- **Adaptive experiences:** enables flexible and relevant user experiences.
- **Process augmentation and transformation:** supports automation and business transformation. This is unlike traditional applications that require lengthy and costly customisation in these circumstances.

The increased adoption of digital technologies has helped organisations cope with the changing needs of customers. The article further states the benefits of using intelligent applications as follows:

- Intelligent applications provide features and results based on one or a combination of AI techniques.
- The continuous learning capability of intelligent applications creates value and disrupts markets.
- The use of applications powered by AI generates new ideas and outcomes and provides deeper insights into business models.

2.4 ANALYTICAL FRAMEWORK

2.4.1 Theoretical Framework

The UTAUT was formulated after the analysis of other theories and models (Venkatesh et al., (2003). From the individual theories and models, seven constructs were significant and deemed a direct determinant of intention or use. This result was determined by analysing the theories and models where these constructs were prevalent in one or more of the models. From this it was theorised that four constructs would play a significant role in determining user acceptance and usage behaviour. The constructs are performance expectancy, effort expectancy, social influence and facilitating conditions. Though formulated from previous models and theories, the labels of each UTAUT construct aims to describe the essence of the construct and is not dependent on any theoretical perspective.

- Performance expectancy**:** Performance expectancy is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh et al., 2003). The five constructs sourced from the various models that support this are perceived usefulness, outcome expectations, extrinsic motivation, job-fit and relative advantage. Performance expectancy is regarded the strongest predictor of intention and is consistent with previous model's tests. This is prevalent where users believe that they will accomplish more tasks and higher quality.

- Effort expectancy: Effort expectancy is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003). To expand further, behavioural intent is strengthened if users find the systems easy, in other words if the work instructions are not complex to accomplish the intended outcome. Three constructs from existing models support this construct of effort expectancy, perceived ease of use, complexity, and ease of use.
- Social influence: Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the new system (Venkatesh et al., 2003). Social influence is seen as a direct determinant of behavioural intent. The construct is labelled as a subjective norm by other theories or social norm. This construct acquires its relevance by the users who believe others will view them positively when discovering they have used a specific technology. (e.g., the use of technology could be used as an incentive to acquire social status.)
- Facilitating conditions: Facilitating conditions are defined as the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system (Venkatesh et al., 2003). The construct is supported by the constructs in three other theories and models, namely perceived behavioural control, facilitating conditions, and compatibility. Simply stated, this construct focuses on the elements that show support from the organisation towards the use of the technology and attending to matters such as a user's self-efficacy in using the technology, training and support provided by the organisation in using the system, and the correlation between the user's job function and the use of the technology.

The UTAUT constructs are key to determining behavioural intention to adopt new technology. The UTAUT model has identified four variables that impact the relationships between the constructs and behavioural intention. namely voluntary use, age, gender, and experience. Venkatesh et al. (2003) emphasised that the moderating variables of the model have the following effects:

- The impact of performance expectancy on behavioural intention is moderated by age and gender, therefore the impact will be higher in males, especially younger males.
- The impact of effort expectancy on behavioural intention is moderated by age, experience, and gender, therefore the impact is higher for females, especially young females and in early stages of the experience.
- The impact of social influence on behavioural intention is moderated by age, experience, gender and voluntariness, and experience, therefore the impact will be higher for women, especially older women and in mandatory settings in the early stages of the experience.
- The impact of facilitating conditions on use is moderated according to age and experience, so that the effect for older employees becomes stronger with increasing experience.

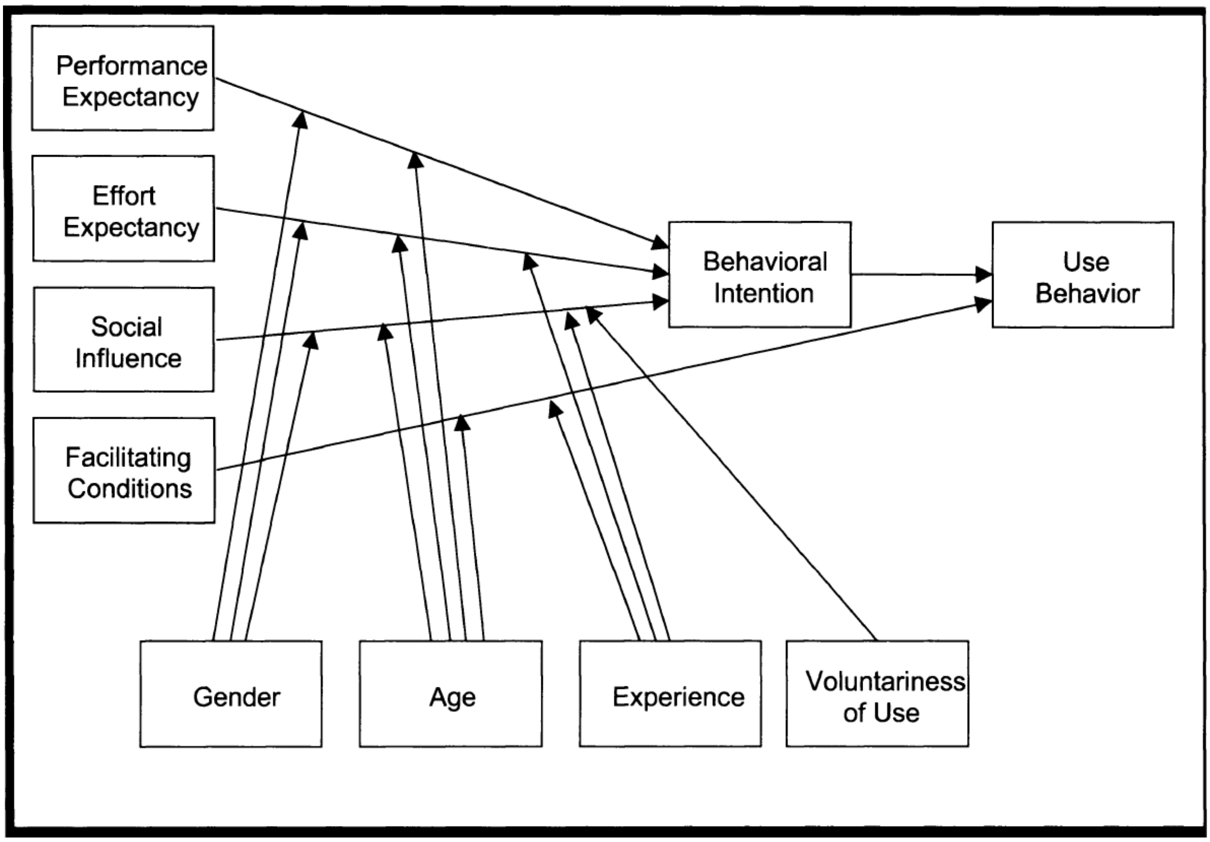

Figure 1 Research Model – Unified Theory of Acceptance and Use of Technology Model

Source: Venatesh et al. (2003)

2.5 HYPOTHESIS DEVELOPMENT AND CONCEPTUAL FRAMEWORK

2.5.1 Conceptual Framework

The conceptual framework provides a visual representation of the hypothesised relationship between the theoretical model constructs and known variables. In this study the extended UTUAT model is used in isolation of other models and frameworks. This is because elements of the extended UTAUT model were derived from TAM framework and TOE model. While UTAUT2 (Venkatesh et al., 2012) extends the original model by including additional constructs such as hedonic motivation, price value, and habit, it is primarily designed for consumer context rather than enterprise systems. In workplace settings—particularly where adoption is often expected or mandated—constructs such as price value are irrelevant since organisations typically bear the cost. Likewise, hedonic motivation is less applicable when tools are used for productivity rather than leisure (Alalwan et al., 2017).

Given that this study focuses on the use of intelligent applications in a professional ICT environment, UTAUT remains a more suitable framework than UTAUT2. The UTAUT model aligns better with the instrumental use of technology and the structured organisational context in which adoption occurs.

The variables of the extended UTAUT (i.e., general awareness, attitude and trust, performance expectancy, effort expectancy, social influence and facilitating conditions) are influenced by variables of age, gender, voluntariness of use and experience. The moderator variables were also amended to examine the effects of moderation on the constructs. This extended the UTAUT model by adding education level, job classification (i.e., managerial/no-managerial) and employment type (i.e., permanent/contractor). The moderator variable, voluntariness of use, has been updated and added as a predictor variable (i.e., general awareness, attitude and trust). This amendment is supported by actual scenarios and studies on digital transformation and the adoption of new technologies, relaying the message that it is not a question if transformation will impact my job or business function, but when will this disruption happen and what extent will the change impact organisations, business functions and employees (Wade et al., 2023). The inclusion of the moderator variable (voluntariness of use) in the UTAUT model would have been relevant prior to the pandemic. However, presently the use and benefits of artificial intelligence tools are known and broadly accepted by employees, hence the exclusion from the study. This is revealed by the statistical analysis in chapter 4. The influence on behavioural intention is likely to be consistent across all business units since each business unit uses a shared system or similar independent systems and processes to provide customer support services to applicable markets, which influences the adoption of intelligent applications.

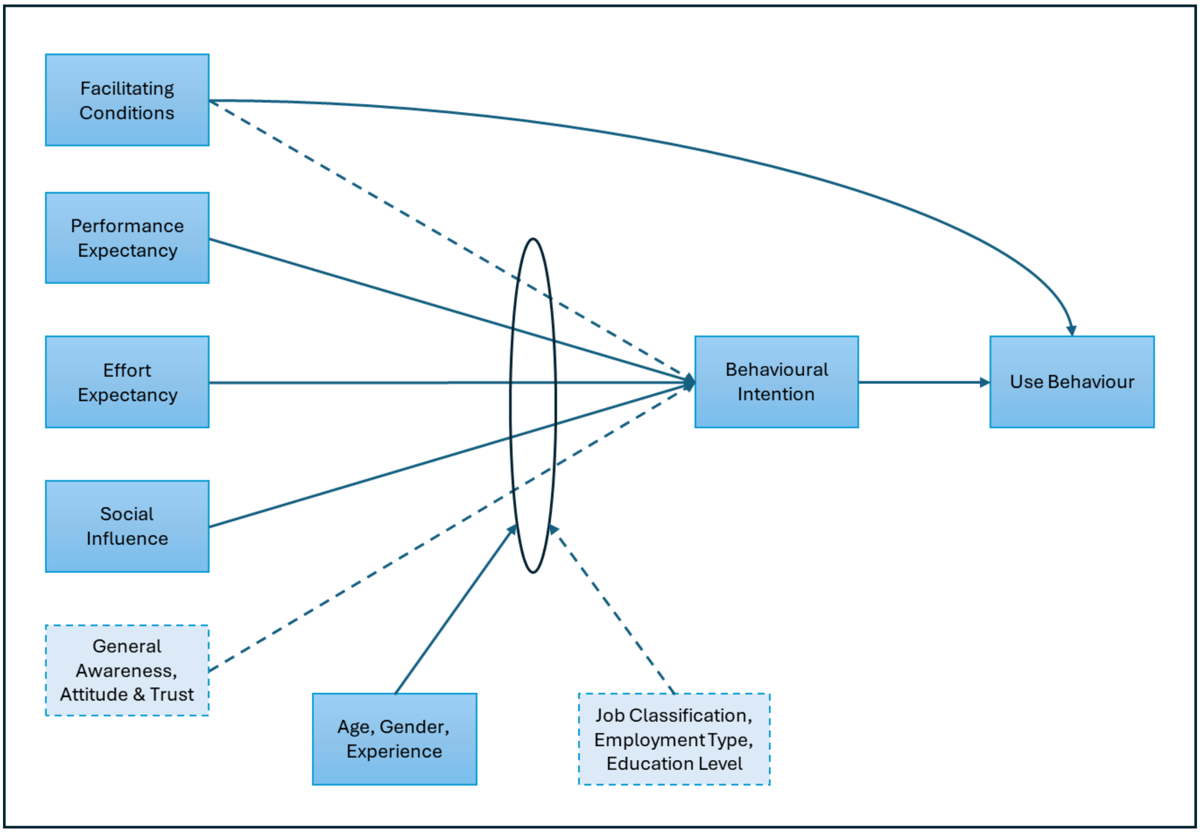

Figure 2 Adjusted Conceptual framework

Source: Researcher

2.5.2 Hypothesis Development

The predictors for this study are general awareness, attitude and trust, performance expectancy, effort expectancy, social influence and facilitating conditions. Though formulated from previous models and theories, the labels of each variable of the extended UTAUT construct aims to describe the essence of the construct and is not dependent on any theoretical perspective. The study aims to contribute to the body of knowledge that is delivered by the additional factors provided by the respondents (i.e., education level, job type (i.e., managerial/non-managerial) and employment type (i.e., permanent/contractor)).

These hypotheses apply to the study:

- **H1:** The predictors of the extended UTAUT model have a significant and positive impact on the behavioural intention to adopt intelligent applications.

- H1a: Performance expectancy is positively associated with behavioural intention to adopt intelligent applications.
- H1b: Effort expectancy is positively associated with behavioural intention to adopt intelligent applications.
- H1c: Social influence is positively associated with behavioural intention to adopt intelligent applications.
- H1d: Facilitating conditions are positively associated with behavioural intention to adopt intelligent applications.
- H1e: General Awareness, Attitude and Trust are positively associated with behavioural intention to adopt intelligent applications.

- **H2:** Age significantly moderates the relationship between the primary constructs and behavioural intention. It is unknown whether age will strengthen or weaken the main relationship.

- **H3:** Gender significantly moderates the relationship between the primary constructs and behavioural intention. It is unknown whether gender will strengthen or weaken the main relationship.

- **H4:** Education level significantly moderates the relationship between the primary constructs and behavioural intention. It is unknown whether education level will strengthen or weaken the main relationship.

- **H5:** Job classification significantly moderates the relationship between the primary constructs and behavioural intention. It is unknown whether job classification will strengthen or weaken the main relationship.

- **H6:** Employment contract significantly moderates the relationship between the primary constructs and behavioural intention. It is unknown whether employment contract will strengthen or weaken the main relationship.

- **H7:** Work experience significantly moderates the relationship between the primary constructs and behavioural intention. It is unknown whether work experience will strengthen or weaken the main relationship.

2.6 CONCLUSION OF LITERATURE REVIEW

In summary, chapter 2 defines the RPA, AI, and intelligent applications technologies. The chapter also provides insight into prior studies conducted in the context of factors influencing the adoption of new technologies. The literature surveys provide a global perspective and a South African perspective on technology adoption to uncover similarities in adoption behaviour. The theoretical framework explains the use of the UTAUT model, and the conceptual framework examines the application and rationale of using an extended UTAUT model for this study.

RPA technology offers many benefits to digital transformation and digital businesses. RPA can break down efficiency barriers in processes by improving process efficiency and reduces limitations introduced by using many applications to produce results. RPA can mimic the behaviour of system users in executing repetitive tasks across multiple systems resulting in reduced errors and inaccuracies in data. As a result, people resources are made available to address more complex problems. RPA can be implemented in a wide range of scenarios provided that the processes are optimised and well defined. The benefits of RPA adoption are complimented by the challenges it presents. Typical examples quoted in several literature articles refer to the ethical and data security considerations of using RPA. The possible solution could be well-structured management of this technology adoption.

AI offers many benefits to digital transformation initiatives. The technology uses algorithms to enable learning and change management. The market in South Africa remains volatile following the COVID-19 pandemic and has not settled completely. In this climate the benefits of implementing AI in organisations could prove beneficial in monitoring the market fluctuations and providing input to strategic decision making at management levels. AI can also be implemented at a customer service level as means of sentiment analysis to determine whether customer channels are meeting the needs of customers and what changes could improve customer experience. AI is currently mostly used in interpreting scanned documents and facial recognition but contains the potential to play a bigger role in the digital business.

Several, more recent, articles from the literature review explore the synergy of AI and RPA. Providing RPA with intelligence to address process improvements and decision-making capabilities that will provide flexibility during execution will give rise to a new area of exploration referred to by Gartner as intelligent applications.

Intelligent applications leverage the strengths of AI, RPA, and disparate data sources to introduce a new technology offering to organisations in South Africa. These technologies in their respective markets have limited application. However, when merged with one another, they can drive greater value delivery to customers, organisations, and system users.

The COVID-19 pandemic has accelerated the need for digital technologies and has driven digital technology adoption by both customers and organisations. Since the pandemic, it has become essential for businesses to adopt digital technologies to continue or even compete in the current commerce market and economic climate.

The rapid pace of technology advancement coupled with the business pressures of cost reduction, driving new revenue streams while improving customer experience prove to be a tricky combination to manage. Adopting intelligent applications could potentially provide for smoother transition from traditional business processes to digital business processes geared to support customers through new digital channels. This capability provides support for the transitioning processes supporting the organisation, employees, and customers in the present and future.

CHAPTER 3: RESEARCH METHODOLOGY

This chapter outlines the research design and methodology used to explore the behavioural factors influencing employee adoption of intelligent applications in Telecom X. The discussion covers the research approach, population and sampling, data collection instrument, and the statistical techniques used to analyse the data.

3.1 RESEARCH APPROACH

This study follows a positivist paradigm and employs a quantitative, cross-sectional research design. The positivist approach supports the use of structured measurement instruments and statistical analysis to test hypothesised relationships between independent and dependent variables (Creswell, 2014). A deductive reasoning approach was used to test hypotheses derived from the extended UTAUT framework. This study requires a substantial number of responses within a limited timeframe. To accomplish this, a survey questionnaire was chosen as a cost-effective method to gather data from various locations within Telecom X across different business units and geographic areas. Despite the respondents being situated around the country, they apply the same processes and function in similar operating environments. This ensures that the respondent’s interaction with the legacy systems remains consistent.

This objective was accomplished in a shorter time frame than would have been possible using a qualitative approach. The target audience primarily consisted of non-management level employees who often represented the customer-facing layer of the business. The analysis was based on factual data to identify causal relationships between non-management user perceptions and their intentions to use intelligent applications, leading to the organisation's adoption of this technology. The study anticipated responses that reflected practical, real-world experiences.

Moreover, the use of online questionnaires ensured respondent anonymity, and encouraged honest and reliable data that yielded valuable insights. These insights helped identify key factors for adopting intelligent applications in customer-facing support operations. Respondents were able to complete the survey without external influence, ensuring that the results reflected an authentic picture of their experiences. Additionally, the survey format allowed respondents the flexibility to complete it at their convenience.

However, the use of online questionnaires presented certain limitations. Respondents were unable to probe further into focus areas or clarify questions, which could potentially skew the study results by limiting the depth of responses and understanding of root causes.

Although the study is not a formal case study in the qualitative sense, the research is situated within a single ICT organisation, which is treated as a methodological case. This organisation was selected due to its digital maturity, national presence, and active integration of intelligent applications across various functions. By framing the organisation as a case context, the study allows for analytical generalisation rather than statistical generalisation.

The nature of the organisation—such as whether it pays for subscriptions, mandates usage, or fosters peer discussions around intelligent applications—can influence employees' perceptions and behaviours. These contextual factors provide a meaningful backdrop for understanding employee adoption dynamics and enhance the explanatory power of the model used.

3.2 RESEARCH DESIGN

Several organisations in South Africa implement decentralised operations for customer services and support. The research followed a deductive research design and used online questionnaires (Creswell, 2014) to collect data from a substantial number of respondents situated across the country. The questionnaire is divided into different parts each focusing on data collection for specific topics as follows:

- **Section A: Demographics.** This section focuses on demographic and biographic information about the respondents. This presents the ability to group the data into categories for analysis and alignment with the extended UTAUT model.
- **Section A1: Understanding of intelligent applications.** This section seeks to determine the respondents' understanding of intelligent applications.
- **Section B1-B6: Perception Measures (extended UTAUT).** This section is extracted from the UTUAT model by Venkatesh et al., (2003) and extended to include general awareness, attitude and trust, and targets the intelligent application adoption factors.

- **Section C:** Additional motivating factors using hypothesised fixed responses and free text comments. This section consists of open-ended questions with limited responses. This section also provides the respondents with the opportunity to voice through free text any additional information that could prove useful in this study.

The survey approach was suited for this study as the objective is to get a generalised view of customer service and support personnel and the factors that influence their behavioural intention to adopt intelligent applications. With technology changes increasing in pace, it is easy to become intimidated by the complex systems and processes. The introduction of intelligent applications provided an opportunity to increase productivity while reducing complexity.

3.3 POPULATION AND SAMPLING

3.3.1 Population

The target population of this study is employees in Telecom X who work in digitally enabled environments where intelligent applications are being deployed. However, the sampling frame consists specifically of employees from the selected case organisation:

- The external staff that work for external organisations and who provide support to the organisation. This includes channel customer service and support.
- The internal staff (permanent employees) who have a support function at the tier two level (advanced level and escalation) and who represent the internal channel between customer service and support teams.
- Operational support staff at the wholesale network business unit.
- Operational support staff at the ICT solution business unit.

3.3.2 Sample and Sampling Method

3.3.2.1 Sample

The sample size was calculated to consist of respondents from three business units of Telecom X. The researcher assumes a confidence level of 95%, a margin of error of 7.5% and a population proportion of 50%. The assumption was based on the respondents having job functions focused on operations or managing teams whose functions are operational in nature. The total headcount for all three business units was 7000, with BU-A and BU-B contributing approximately 5000 potential respondents. A total of 160 responses were received and included in the analysis. Respondents represented a cross-section of departments, job roles, and education levels within the organisation.

- Gender: e.g., 52% female, 48% male
- Job Classification: e.g., 40% operational, 35% technical, 25% support
- Contract Type: e.g., 80% permanent, 20% temporary
- Education Level: e.g., 45% undergraduate, 35% honours, 20% postgraduate

This diversity supports the generalisability of findings within the organisational context.

The sample size is calculated using the formula below:

Confidence level (Z): 1.96 (95%)
Margin of error (E): 7.5%
Population proportion (standard deviation) (P): 50%
Population size (N): 7000

$$SS = \frac{\frac{Z^2 \text{ x } P(1-P)}{E^2}}{1} + \left(\frac{Z^2 \text{ x } P(1-P)}{E^2}\right)$$

$$SS = \frac{\frac{(1.96)^2 \text{ x } 0.5(1-0.5)}{(0.075)^2}}{1} + \left(\frac{(1.96)^2 \text{ x } 0.5(1-0.5)}{(0.075)^2 \text{ x } (7000)}\right)$$

SS ≈ 167

3.3.2.2 Sampling Method

This research method used the technique of simple random sampling. The simple random sampling technique gave the researcher the flexibility to select respondents for the study without bias and at random. The total population of ICT company employees, including the employees in the business units, were eligible to participate in the study.

Simple random sampling presents several benefits and drawbacks according to the authors of the article by Noor et al., (2022). The technique favours studies where the population is homogenous, and participants randomly selected. It not suited for population studies where the sample is widely dispersed.

The total number of respondents was 178. A non-probability sampling approach was used. This consisted of a combination of purposive (i.e., sample people selected on purpose) and convenient (i.e., access to the target group being part of the same organisation) sampling and snowball sampling methods (Greener, 2008). This approach was used to target those groups where there was a higher likelihood of getting responses that are relevant and useful for the study. Feedback was obtained through a network of colleagues and managers, at various organisational levels, within the same business unit. Data was collected from staff from other business units serving the same function so that there was a good representation of customer service and support personnel across the organisation. The target sample size is at least 167 responses to provide for meaningful analysis.

3.4 DATA COLLECTION METHODS AND PROCEDURES

An online questionnaire was the instrument of choice to gather insights of the extended UTAUT predictors (general awareness, attitude and trust, performance expectancy, effort expectancy, social influence and facilitating conditions) and variables (gender, age, and experience). Using Qualtrics, an anonymous link was created to access the online questionnaire and was distributed to customer service representatives and support personnel via the researcher's company email account. Using Qualtrics to facilitate the survey allowed for the storage, retrieval and high-level analysis of data electronically using the Qualtrics online platform. A five-point Likert scale was used to capture the inputs from respondents and provided a simplified response mechanism for respondents to complete. The Likert scale was applicable to the perception measures section of the survey and was as follows:

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree

- Strongly agree

Open-ended questions provided the respondents with an opportunity to submit additional insights to topic (i.e., barriers and enablers) which had a significant contribution to aligning the statistical analysis findings to recommendations for future studies.

Data were also collected from customers facing support personnel that are within the researcher’s network by requesting them to participate and by distributing the survey email to other personnel in customer services, within their networks, to participate. This was done by sending emails with a link to the survey directly to this network and asking them to share it with their network’s participants in customer services. All data were primary data and included demographic data to enhance insightful analysis and results. The online questionnaire did not collect respondent’s personal information as this was not required for the analysis. The data collected were statistically analysed by Jamovi (Version 2.0, Computer Software, 2023).

3.5 THE RESEARCH INSTRUMENT

The online questionnaire approach administered by Qualtrics was used to collect data. The questionnaire structure included a combination of custom questions and questions targeting the criteria aligned with the extended UTAUT model.

Survey Structure:

- Section A: Demographics (Captured job classification, contract type (permanent/temporary), education level, and experience with digital tools.)
- Section A1: Understanding intelligent applications (Captured the respondent’s understanding of Intelligent Applications)

  Section B1-B6: Perception measures (Items were adapted from validated instruments in previous research (Venkatesh et al., 2003)). All items used a 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

Construct	Number of Items	Sample Question	Cronbach Alpha
Performance Expectancy	6	Using intelligent applications improves my job performance.	0.930

Effort Expectancy	6	Learning to use intelligent applications is easy for me.	0.857
Social Influence	7	People who influence my behaviour think I should use intelligent applications.	0.870
Facilitating Conditions	5	I have the resources necessary to use intelligent applications.	0.841
General Awareness, Attitude and Trust	10	I am aware of the intelligent applications used in my department.	0.888
Behavioural Intention	3	I intend to use intelligent applications regularly in my work.	0.768

- Section C: Included two open-ended prompts using the divergent questioning technique to identify perceived barriers and enablers of adoption.

The questions for the survey were formulated by referencing Creswell (2014) and modified by the researcher to align with the topic. Items for each construct were averaged to produce composite scores. Spearman’s rank correlation was used due to the ordinal nature of Likert scale data.

3.6 DATA ANALYSIS

The responses were analysed using open-source statistical analysis software for the Social Sciences (Jamovi (Version 2.0, Computer Software, 2023)). The extended UTAUT model examined whether a relationship existed between dependant variable and independent variables. In this study the dependent variable was behavioural intention influenced by independent variables (general awareness, attitude and trust, performance expectancy, effort expectancy, facilitating conditions and social influence). According to Creswell (2014) a multiple linear regression analysis approach was used to examine the relationships between variables.

The extended UTAUT model predictors also determined the influence of moderator variables on the relationship between the predictors and the dependent variable. Moderator variables were age, gender, job classification, employment contract type, education level, and work experience. This allowed the researcher to determine how the results differ based on the different moderators. A thematic analysis technique was used to analyse the responses to the open-ended questions in the questionnaire. This method revealed key themes that aligned with the results of the statistical analysis.

The following analysis procedures were performed on the data collected:

- Descriptive Statistics: Frequencies, means, and standard deviations were calculated to profile the sample.
- Reliability Testing: Cronbach's alpha was reported for each construct.
- Construct Aggregation: Items for each construct were averaged to produce composite scores.
- Correlation Analysis: Spearman's rank correlation was used due to the ordinal nature of Likert scale data.
- Multiple Linear Regression:
  Conducted to examine the influence of the independent variables (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Awareness, Attitude and Trust) on the dependent variable (Behavioural Intention).
  - Standardised beta coefficients were reported.
  - Model fit was assessed using R^2, adjusted R^2, F-statistics, and significance level ($p < 0.05$).
- Moderation Analysis:
  Moderator variables (job classification, contract type, education level) were tested through interaction terms in separate regression models.
  - All variables involved in interaction terms were mean centred before computation.
  - Where moderation was significant, the direction of moderation was interpreted using simple slopes plotting (low, medium, high moderator levels).

3.7 VALIDITY AND RELIABILITY

The UTAUT model is reliable due to its adoption in research studies by several researchers over many years. The UTAUT 2 model, not suitable for this study, presents a personalised focus by exploring other variables that could give deeper meaning when understanding the user acceptance of technologies where the user pays for the application or receives personnel gratification from the use of the intelligent application. For this study, the UTAUT model was extended to explore other factors that potentially influenced the adoption of new technology.

3.7.1 Validity

The UTAUT model is a popular model in determining the factors for the adoption of new technologies. The system users were situated across the organisation but shared a common interest in providing a service to customers, whether internal or external. The term “customer” was used loosely in this study and could mean either “external customers” (i.e., the people or organisations who buy products from the organisation) or “internal customers” (i.e., the people or organisations who require products and services from sections within the organisation). The questionnaire was directed to system users in a support or service role whether interacting with internal or external customers. This ensured that respondents had a consistent understanding of the questions. The questionnaire used the same structure as previous studies, except those intelligent applications was the technology examined in this study at a point in time.

The work was done under the guidance of a supervisor who had prior experience in research related to the use of new technology in various economic sectors.

3.7.2 Reliability

The UTAUT model has been widely employed across diverse industries and technologies for assessing user intention to adopt new or emerging technologies. The UTAUT model’s established framework makes it a preferred choice in research endeavours. In this study, the UTAUT model was extended to explore other factors that potentially influenced the adoption of new technology. The researcher aimed to replicate parts of this model to uncover new trends and factors that influence adoption. The secondary aim was to inform potential future research areas. The model was assessed for reliability using the Cronbach Alpha coefficient, a standard method for testing internal consistency. The data limitations were specific to South Africa, hence validating the findings of the data with low accuracy may pose challenges. The researcher planned to compare the results with the results of studies utilising the conceptual extended UTAUT model to enhance credibility and robustness.

3.8 LIMITATION

The retail services, wholesale and network services, ICT solutions and services, business unit managers were responsible for sending communication to their peers and employees to participate in the survey. This method ensured that information security standards were maintained. This method also ensured that the anonymity of employees was protected. Therefore, reminder emails prompting individuals to participate in the survey was not possible.

Using intelligence applications in the ICT sector was assumed to be limited. This occurrence in turn had limited the results of the online questionnaire. While the organisation does employ the use of RPA technology in limited scenarios, the use of technologies employing AI was limited. There are limited studies, empirical in design, conducted on intelligent applications in ICT, in both the South African and globally context. This posed challenges when comparing results. Intelligent applications are a combination of a few digital technologies; therefore, the comparison was conducted using RPA and AI since both technologies form part of intelligent applications.

3.9 ETHICAL CONSIDERATION

The research was conducted using an online survey, which was voluntary for participants. Before commencing with the survey, participants were presented with a cover page where they had to provide their consent before participating in the survey. Assurance was given about the anonymity of the survey and that participants could withdraw from the study at any time. In addition, the contact details of the researcher and supervisor were published on the cover page in the event of queries or clarifications. No personal data were collected from respondents, and all responses were used strictly for academic research purposes. The study adhered to the guidelines set by the Wits Business School (WBS). The ethics form and guidelines document from WBS was completed to ensure ethical standards were met throughout the research process.

3.10 ANTICIPATED CONTRIBUTION OF THE STUDY

There are limited empirical studies of the adoption of intelligent applications in the South African ICT industry context. The volume of studies in digital technology adoption has increased since the COVID-19 pandemic. From the literature survey, most studies focused on the adoption of a single digital technology and associated use cases in various economic sectors. Technology evolution is ongoing and now includes convergence of digital technologies. The technology convergence events developed a wider range of use cases and application scenarios. Considerations such as privacy, ethics, business operations and customer experience have become more dynamic including the adoption constructs. The findings of this research study contribute to the body of knowledge for the technology adoption using the extended UTAUT model.

3.11 CONCLUSION

The methodology of this study is summarised as follows:

- Research design and method: Empirical quantitative technique
- Population and sampling: SA ICT sector, customer facing system users.
- Data collection: Online surveys distributed via email.
- Data analysis: Jamovi Statistical Analysis Software
- Validity and reliability: UTAUT

CHAPTER 4: KEY RESULTS AND FINDINGS

4.1 SAMPLE

A structured questionnaire, distributed online, was the research instrument used to collect data for this cross-sectional study in which the sample pool was made up of respondents from a South African organisation in the information and communications technology (ICT) industry comprising of various business units. Within each business unit the study focused on the respondents from the customer support function. Customer support, in the context of this study, is a service function provided by the organisation to both internal (people from departments within the organisation) and external (people from outside the organisation) business customers.

4.2 DATA PREPARATION

A total of 178 responses were collected. Cases with missing values exceeding 50% (n = 18) were excluded from the analysis. Therefore, 160 responses were used for the statistical analysis.

To run the moderated regression analysis, certain groups were merged due to the small sample sizes in specific categories:

- Age: Respondents aged 20 and under were merged with those aged 21–30, resulting in a new category, "Under 30." Similarly, the "51–60" and "Above 60" age groups were combined into a new category, "51 and Above."
- Education: Respondents with "Master’s" and "PhD" qualifications were combined into a single category.

4.3 DESCRIPTIONS

The descriptions used in the data analysis is detailed in table 1.

Table 1 Item descriptions

Item Description	**Count (N)**
In which business unit do you currently work?	160
Please indicate your age?	160

Please indicate your gender?	160
Please indicate your highest education level?	160
Please indicate if you are in a management or operational position?	160
Are you a permanent employee or contractor?	160
Please provide the number of years you have worked for the company.?	160
How would you characterise your overall understanding of computer programs?	160
How do you rate your knowledge of intelligent applications?	160
How long have you been using intelligent applications?	160

4.4 FREQUENCIES

4.4.1 Business Unit

The number of respondents per business unit are shown in table 4.2. below. Permission was attained from the various business units. The names of the business units have been masked by assigning pseudonyms to each. This was necessary as the permission letter stipulated that the name of the organisation and the business units must not be stated in the final report on the study.

BU-A is a business unit that focuses its operations on retail services (i.e., direct to customer) and services the volume/mass market. BU-B is a business unit that focuses its operations on wholesale and network services and operates in the business-to-business market. BU-C is a business unit that focuses its operations on ICT solutions and services the enterprise market. BU-D is situated at group level that focuses its operations on governance and compliance within the organisation.

Most of the respondents were from the BU-A business unit due to the researcher being stationed in the same business unit and therefore familiar with the organisational layout as opposed to the other business units.

Table 2 Respondents per business unit

Business Unit	Count (N)	% of Total	Cumulative %
BU-A	75	46.9%	46.9%
BU-B	40	25.0%	71.9%
BU-C	32	20.0%	91.9%
BU-D	13	8.1%	100.0%

4.4.2 Age

Table 3 outlines the age distribution of 160 respondents. The data shows that most respondents are between the ages 31 and 60 (134 representing 83.7%, with the 41–50 age group representing the highest contribution to the dataset (31.9%). Age groups 31–40 and 51–60 are similar amounts having 40 and 43 (25% and 26.9% respectively).

Table 3 Respondents per age group

Age Group	Count (N)	% of Total	Cumulative %
20 or under	1	0.6%	0.6%
21 – 30	17	10.6%	11.3%
31 – 40	40	25.0%	36.3%
41 – 50	51	31.9%	68.1%
51 – 60	43	26.9%	95.0%
61 and above	8	5.0%	100.0%

4.4.3 Gender

Table 4 provides a breakdown of gender distribution of the 160 respondents. This shows a nearly equal distribution of males and females, with a small percentage opting not to disclose their gender.

Table 4 Respondents per gender

Age Group	Count (N)	% of Total	Cumulative %
Male	80	50.0%	50.0%
Female	79	49.4%	99.4%
Prefer not to say	1	0.6%	100.0%

4.4.4 Education Qualification

Table 5 outlines the various educational qualifications for the 160 respondents, revealing a diverse range of academic backgrounds.

- Matric holders, at 11 respondents (6.9%), represent those with secondary-level education, the smallest group among standard qualifications.
- Diplomas are also prominent, with 33 respondents (20.6%), indicating a significant proportion opted for vocational or practical training.
- Bachelor’s degrees are the most common qualification, held by 45 respondents (28.1%), highlighting the prevalence of graduate education in the group.
- Honours degrees follow closely, with 38 respondents (23.8%), suggesting that nearly a quarter of the participants pursued postgraduate studies.
- Master’s degrees account for 24 respondents (15%), reflecting the pursuit of advanced postgraduate education by a notable segment of the population.
- Doctorates, with only two respondents (1.3%), highlight the rarity of the highest academic attainment in this sample.
- Other qualifications, accounting for seven respondents (4.4%), point to less common or alternative educational pathways.

This distribution emphasises the dominance of higher education (bachelor and honours degrees) among the respondents, with relatively fewer individuals holding matric, doctorates, or other qualifications.

Table 5 Respondents per education level

Qualification	Count (N)	% of Total	Cumulative %
Matric	11	6.9%	6.9%
Diploma	33	20.6%	27.5%
Bachelor’s degree	45	28.1%	55.6%
Honours degree	38	23.8%	79.4%
Master’s degree	24	15.0%	94.4%
Doctorate	2	1.3%	95.6%
Other	7	4.4%	100.0%

4.4.5 Type of Job Function

Table 6 outlines the job functions of 160 respondents, highlighting the distribution between management and non-management roles:

- Management roles dominate, with 86 respondents (53.8%), indicating that over half of the participants hold positions involving leadership, decision-making, and strategic oversight.
- Non-management roles account for 74 respondents (46.2%), representing those focused on the day-to-day execution of tasks and processes essential to organisational functioning.

The distribution suggests a relatively balanced representation, though there is a slight tilt towards management roles, reflecting a sample that includes a significant proportion of decision-makers and leaders.

Table 6 Respondents per job function group

Job Role	Count (N)	% of Total	Cumulative %
Management	86	53.8%	53.8%
Non-management	74	46.3%	100.0%

4.4.6 Employment Contract Type

Table 7 provides an overview of the employment types among 160 respondents, highlighting the distinction between permanent and contractual work arrangements:

- Permanent employment is the predominant type, with 125 respondents (78.1%), signifying job stability and long-term commitment for most participants.
- Contractors, accounting for 35 respondents (21.9%), represent a smaller but notable segment, indicative of temporary or project-based roles.

The distribution underscores a workforce primarily composed of permanent employees, with a smaller proportion engaged in flexible or short-term contracts, which could reflect organisational reliance on a stable workforce supplemented by contractors as needed.

Table 7 Respondents per employment contract type

Employment Contract Type	Count (N)	% of Total	Cumulative %
Permanent employees	125	78.1%	78.1%
Contractors	35	21.9%	100.0%

4.4.7 Years of Experience

Table 8 presents the distribution of respondents based on their years of professional experience, revealing a wide range of tenure:

- Seven respondents (4.4%) have less than two years' experience, representing newcomers to the workforce.
- Those with 2–5 years of experience account for 33 respondents (20.6%), followed closely by 6–10 years, with 31 respondents (19.4%), reflecting a substantial representation of early to mid-career professionals.
- 11–15 years of experience is held by 19 respondents (11.9%), and 16–20 years by 17 respondents (10.6%), indicating a steady presence of mid-career individuals.
- More than 20 years of experience is the largest group, with 53 respondents (33.1%), showcasing a significant proportion of highly seasoned professionals.

This distribution highlights a workforce skewed towards seasoned professionals, with over a third having more than 20 years of experience, complemented by a significant presence of those in the early and mid-stages of their careers.

Table 8 Respondents years of experience

Years of Experience	Count (N)	% of Total	Cumulative %
Less than 2 years	7	4.4%	4.4%
2–5 years	33	20.6%	25.0%
6–10 years	31	19.4%	44.4%
11–15 years	19	11.9%	56.3%
16–20 years	17	10.6%	66.9%
More than 20 years	53	33.1%	100.0%

4.4.8 Knowledge of Computer Applications

The table illustrates the level of knowledge about intelligent applications among 160 respondents, reflecting varying degrees of familiarity and expertise:

- Basic knowledge is held by 21 respondents (13.1%), representing those with an introductory or foundational understanding.
- Proficient knowledge is the most common, reported by 82 respondents (51.2%), indicating that a majority possess an understanding of intelligent applications.
- Advanced knowledge is demonstrated by 57 respondents (35.6%), highlighting a significant segment of highly skilled and experienced individuals in this domain.

This distribution suggests a workforce primarily well-versed in intelligent applications, with a notable proportion demonstrating advanced expertise and a smaller group at the basic level, indicating varying opportunities for further training and development.

Table 9 Respondents' computer knowledge

Knowledge of computer programs	Count (N)	% of Total	Cumulative %
Basic	21	13.1%	13.1%
Proficient	82	51.2%	64.4%
Advanced	57	35.6%	100.0%

4.4.9 Knowledge of Intelligent Applications

Table 4.10 describes respondents' levels of knowledge about intelligent applications, revealing a spectrum of expertise:

- Basic knowledge is reported by 39 respondents (24.4%), suggesting a significant group with foundational familiarity but likely in need of further training.
- Proficient knowledge is the most prominent, with 88 respondents (55%), indicating that over half of the participants have a solid working understanding of intelligent applications.

- Advanced knowledge is held by 32 respondents (20%), showcasing a smaller but substantial segment of highly skilled individuals.
- Not applicable is selected by one respondent (0.6%), indicating irrelevance of intelligent applications to their context.

This data highlights a workforce where the majority are either proficient or advanced in their understanding of intelligent applications, with a notable portion at the basic level, reflecting potential opportunities for skills development.

Table 10 Respondents knowledge of intelligent applications

Knowledge of intelligent applications	Count (N)	% of Total	Cumulative %
Basic	39	24.4%	24.4%
Proficient	88	55.0%	79.4%
Advanced	32	20.0%	99.4%
Not Applicable	1	0.6%	100.0%

4.4.10 Experience in using Intelligent Applications

Table 11 provides insights into respondents' experience with intelligent applications, reflecting varied levels of engagement:

- Never using intelligent applications is reported by seven respondents (4.4%), reflecting minimal exposure within the sample.
- Sometimes using intelligent applications is the most common response, with 64 respondents (40%), indicating moderate and occasional exposure to these technologies.
- Those engaging with intelligent applications about half the time account for 37 respondents (23.1%), suggesting a balanced mix of tasks involving these tools.
- Most of the time is reported by 35 respondents (21.9%), representing a significant group with frequent usage of intelligent applications in their work.
- Always using intelligent applications is noted by 17 respondents (10.6%), highlighting a smaller, consistent user base.

This distribution suggests a wide spectrum of familiarity, with a substantial majority using intelligent applications at least part of the time, but only a small fraction utilising them consistently.

Table 11 Respondents experience with intelligent applications

Experience with intelligent applications	**Count (N)**	**% of Total**	**Cumulative %**
Never	7	4.4%	4.4%
Sometimes	64	40.0%	44.4%
About half the time	37	23.1%	67.5%
Most of the time	35	21.9%	89.4%
Always	17	10.6%	100.0%

4.5 DESCRIPTIVE STATISTICS

The table below presents model fit statistics influencing the adoption of intelligent applications in Telecom X.

Model Fit Measures

Model fit measures were conducted to determine how well the data is described by the regression model. This is important for the accuracy assessment of the statistical model.

The overall F-test indicates that the model is statistically significant **F (28.7), df1 (5), df2 (151), ($p<0.001$)** meaning at least one of the predictors contributes significantly to the model.

The model explains that **48.7% (R^2 = (0.487) *100)** of the variance in behavioural intention is determined by one or more independent variables. This is explained by the predictors (general awareness, attitude and trust, performance expectancy, effort expectancy, social factors, and facilitating conditions).

Table 12 Model Fit Measures

	Overall Model Test

Model	R	R^2	F	df1	df2	p
Model Fit Measures	0.698	0.487	28.7	5	151	<.001

Note. Models estimated using sample size of N=157

The table below presents descriptive statistics for six key factors influencing the adoption of intelligent applications in Telecom X. These factors include general awareness, attitude and trust, performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention. Each factor is assessed based on sample size (N), mean, median, standard deviation (SD), skewness, standard error of skewness (SE), and normality tests (Shapiro-Wilk test).

Table 13 Descriptive Statistics

						Skewness		Shapiro-Wilk	
	N	Missing	Mean	Median	SD	Skewness	SE	W	p
General awareness, attitude and trust	160	0	4.12	4.20	0.634	-1.286	0.192	0.908	<.001
Performance expectancy	160	0	4.30	4.33	0.734	-1.858	0.192	0.816	<.001
Effort expectancy	160	0	4.19	4.17	0.660	-1.305	0.192	0.900	<.001
Social factors	159	1	3.73	3.71	0.737	-0.454	0.192	0.973	0.003
Facilitating conditions	157	3	3.62	3.80	0.795	-0.613	0.194	0.967	<.001
Behavioural intention	157	3	4.00	4.00	0.786	-0.688	0.194	0.931	<.001

The factors of general awareness, attitude and trust, performance expectancy and effort expectancy record mean and median score of 4 and higher indicating that respondents were generally positive towards intelligent applications. social influence and facilitating conditions score a lower mean and median score (4>score>3) indicating that these factors have a weaker influence on intelligent applications adoption.

The standard deviation for all factors suggests a moderate variability in response. The lowest variability being 0.634 (general awareness, attitude and trust) and the highest from 0.795 (facilitating conditions).

The skewness value indicates varying degrees of negatively skewed distribution. The highest skewness value being -1.858 (Performance Expectancy) showing a strong left skew. The lowest value being -0.454 (social influence) showing a symmetrical distribution closer to zero. The consistent negative values observed across all variables indicate that responses are generally positive towards intelligent applications adoption.

4.5.1 General Awareness, Attitude and Trust between Intelligent Applications and Customer Services

The analysis suggests that respondents perceive intelligent applications as valuable, particularly for repetitive and structured tasks. This is consistent for respondents who also perceive that intelligent application will complement the customer services business function in future. Trust and adoption, while significant, have a lower score when addressing cognitive functions and strategic implementation. Table 13 details each item of the general awareness, attitude and trust construct.

Table 14 Descriptive Analysis - General Awareness, Attitude and Trust

Number	**Item (Observed)**	**Mean**	**Standard Deviation**
B1.1	I believe that intelligent applications will provide value when performing my job function.	4.26	0.872
B1.2	I like to use an intelligent application when performing my tasks.	4.23	0.906
B1.3	I trust the results provided from an intelligent application when performing my tasks.	3.86	0.955
B1.4	I feel comfortable working with intelligent applications?	4.19	0.850
B1.5	I believe that using intelligent applications to perform my tasks will reduce cost for the company.	4.06	1.011
B1.6	Real-time assurance (i.e., customer / end-user support) will be possible with intelligent applications.	4.20	0.845
B1.7	In my opinion, intelligent applications will outperform manual activities in delivering dependable outcomes for repetitive jobs and	4.37	0.814

	tasks involving the utilisation of numerous intricate systems.		
B1.8	I believe that intelligent applications will be able to provide reliable results that require cognitive functions such as the application of professional judgement when providing feedback to customers.	3.78	1.050
B1.9	I believe that intelligent applications will be used to complement the work of customer service agents in the future.	4.42	0.723
B1.10	My organisation is currently using or planning to use intelligent applications as part of its strategic goals.	3.77	0.925

4.5.2 Performance Expectancy

Table 14 presents the descriptive analysis of performance expectancy, examining respondents' perceptions of how intelligent applications enhance efficiency, productivity, and overall work performance. The resulting analysis indicates a strong positive perception of intelligent applications in improving work efficiency, reducing errors, and freeing up time for more complex tasks. The highest score was observed for task completion speed having a score of 4.53. The next equally ranked positive perception was for time saving and error reduction having an equal score 4.24 after usefulness in customer services. The table below details each item of the performance expectancy construct.

Table 15 Descriptive Analysis - Performance Expectancy

Number	Item (Observed)	Mean	Standard Deviation
B2.1	Intelligent applications are useful in the customer service environment.	4.36	0.755
B2.2	Intelligent applications enable customer service agents to accomplish tasks more quickly.	4.53	0.672
B2.3	Using intelligent applications in my job will save a significant amount of time.	4.24	0.921
B2.4	Using intelligent applications would help me perform better by reducing potential errors.	4.19	0.908
B2.5	I will add more value to my work by using intelligent applications.	4.24	0.874
B2.6	Having intelligent applications could free up my time so I can work on other projects.	4.22	0.956

4.5.3 Effort Expectancy

Table 15 presents the descriptive analysis of effort expectancy, which examines respondents' perceptions of the ease of use, learning curve, and technical skills required to effectively use intelligent applications in the workplace. The observed responses provide a positive perception associated with intelligent applications, with respondents expressing enjoyment in learning about new technologies and confidence in their ability to use them. Variability regarding reskilling/upskilling are also observed. The table below details each item of the effort expectancy construct.

Table 16 Descriptive Analysis - Effort Expectancy

Number	Item (Observed)	Mean	Standard Deviation
B3.1	I enjoy learning about how to leverage the benefits of using various technologies in my job.	4.53	0.752
B3.2	I consider intelligent applications is easy to use.	4.13	0.775
B3.3	Using intelligent applications reduces the time to upskill / reskill employees.	3.96	1.015
B3.4	I have the technical skills needed to use an intelligent application in performing my job functions.	4.16	0.882
B3.5	Adopting process changes in customer service is made simpler by the use of intelligent applications.	4.14	0.865
B3.6	Using an intelligent application will make my work easier.	4.22	0.876

4.5.4 Social Influence

Table 16 below provides an analysis of social influence, which explores how external social factors, such as organisational support, peer influence, and managerial encouragement have an impact on the adoption and usage of intelligent applications in the workplace. The analysis suggests that social influence plays a significant role in determining the adoption of intelligent application in Telecom X. However, the support received for the adoption of intelligent applications varies. External partners and customers have stronger influence when adopting new technologies. The table below details each item of the social influence construct.

Table 17 Descriptive Analysis - Social Influence

Number	Item (Observed)	Mean	Standard Deviation
B4.1	My organisation supports the use of intelligent applications in my job.	3.81	0.894
B4.2	Using an intelligent application at work would elevate me to having a higher social status than those who do not.	3.39	1.102
B4.3	My friends/family support the use of intelligent applications both socially and professionally.	3.71	1.045
B4.4	My manager supports the use of intelligent applications in my job.	3.87	0.929
B4.5	Using an intelligent application in my job will advance my career progression (promotions, opportunities, remuneration, etc.).	3.65	1.115
B4.6	The teams that I support encourage the use of intelligent applications.	3.81	0.894
B4.7	The expectations of my business partners / clients are that support functions should employee the use of intelligent applications.	3.89	0.876

4.5.4 Facilitating Conditions

Table 17 provides an analysis of facilitating conditions, examining how respondents perceive the organisational and external conditions that support the adoption and use of intelligent applications in their jobs. Respondents perceive some organisational structures and external initiatives as supportive. There is a notable gap in financial resources and support systems necessary for effective learning and usage of intelligent applications. The table below details each item of the facilitating conditions construct.

Table 18 Descriptive Analysis - Facilitating Conditions

Number	Item (Observed)	Mean	Standard Deviation
B5.1	My organisation has structures to support learning and understanding the use of intelligent applications.	3.71	1.050

B5.2	There are government and country-wide initiatives across South Africa that supports the use of intelligent applications in support services.	3.69	0.931
B5.3	My organisation has the necessary funds available for me to learn or use intelligent applications in performing my job function.	3.45	1.077
B5.4	My organisation has the necessary skills to start using intelligent applications.	3.68	1.008
B5.5	I have access to the relevant support should I need help when problems are encountered while using intelligent applications.	3.56	1.015

4.5.5 Behavioural Intention

Table 18 provides an analysis of behavioural intention, examining respondents' future intentions regarding the adoption and use of intelligent applications (IAs) in customer support work. The analysis of behavioural intention reveals a generally positive outlook towards the adoption of intelligent applications in customer support roles. Respondents exhibit strong intention to learn how to use intelligent applications. The table below details each item of the behavioural intention construct.

Table 19 Descriptive Analysis - Behavioural Intention

Number	Item (Observed)	Mean	Standard Deviation
B6.1	I intend using intelligent applications in performing customer support work in the next 12 months.	3.80	1.011
B6.2	I predict that intelligent applications will be used in my organisations for performing customer services in the next 24 months.	3.89	0.997
B6.3	I intend learning to use intelligent applications in the next 12 months.	4.30	0.836

4.6 CORRELATION ANALYSIS

The Spearman Correlation Analysis was performed on the dataset to determine whether a relationship exists among the independent variables. The Spearman's rank correlation is a non-parametric test used to assess the strength and direction of association between two independent variables, based on the ranks of the values.

Spearman’s rank correlation was used due to the ordinal nature of Likert scale data. The correlation matrix provides more details on the results of the test.

4.6.1 Correlation Matrix

The correlation matrix presents the results of a Spearman correlation analysis conducted on several independent variables from the survey. The independent variables analysed include general awareness, attitude and trust, performance expectancy, effort expectancy, social factors, facilitating conditions, and behavioural intention. The results consistently suggest that the likelihood of individuals intending to engage with new technology increases as general awareness, attitude and trust, performance expectancy, and facilitating conditions increase. The strong correlations between facilitating conditions and behavioural intention stand out from the correlation among other independent variables. These findings contribute to the growing body of research examining the factors influencing technology acceptance and use, offering valuable insights for practitioners seeking to improve adoption rates through enhancing users' perceptions of performance, ease of use, and the support available.

Table 20 Correlation Matrix

	General Awareness, Attitude and Trust	Performance expectancy	Effort expectancy	Social Factors	Facilitating conditions	Behavioural intention
General Awareness, Attitude and Trust	—					
Performance Expectancy	0.755***	—				
Effort Expectancy	0.619***	0.710***	—			
Social Factors	0.570***	0.582***	0.581***	—		
Facilitating conditions	0.329***	0.389***	0.425***	0.562***	—	
Behavioural intention	0.491***	0.454***	0.416***	0.524***	0.602***	—

*Note. * p < .05, ** p < .01, *** p < .001*

Correlation analysis was performed to determine if there is a significant association between general awareness, attitude and trust, performance expectancy, effort expectancy, social factors, facilitating conditions, and behavioural intention. The Spearman correlation was performed to identify the strength and direction of the relationships between the independent variables. The detailed interpretation is as follows:

1. **General Awareness, Attitude, and Trust vs. Other Factors**

There is a strong positive correlation ($r=0.755$, $p<0.001$) suggesting that higher general awareness, attitude, and trust are associated with higher performance expectancy.

A moderately strong positive correlation ($r=0.619$, $p<0.001$) indicates that better awareness and trust are associated with reduced effort expectancy.

A moderately positive relationship ($r=0.570$, $p<0.001$) indicates that social influences are moderately linked to general awareness, attitude and trust.

A weak positive correlation ($r=0.329$, $p<0.001$) suggests a limited relationship between general awareness, attitude and trust, and facilitating conditions.

A moderate positive correlation ($r=0.491$, $p<0.001$) shows that better awareness and trust are somewhat linked to stronger behavioural intentions.

2. **Performance Expectancy vs. Other Factors**

Correlates strongly with effort expectancy ($r=0.710$, $p<0.001$), moderately correlated with social factors ($r=0.582$, $p<0.001$) and weakly with facilitating conditions ($r=0.389$, $p<0.001$), indicating some influence of these on performance expectancy. Moderately correlated with behavioural intention ($r=0.454$, $p<0.001$),

3. **Effort Expectancy vs. Other Factors**

Strongly to social factors ($r=0.582$, $p<0.001$) and weakly to facilitating conditions ($r=0.425$, $p<0.001$). Shows a moderate positive relationship with behavioural intention ($r=0.416$, $p <0.001$), indicating the ease-of-use influences intent to act.

4. **Social Factors vs. Other Factors**

Correlates moderately with behavioural intention ($r=0.562$, $p<0.001$), showing the importance of social influence on intentions. Weak to moderate correlations with facilitating conditions ($r=0.524$, $p<0.001$),

5. **Facilitating Conditions vs. Other Factors**

The strongest correlation is with behavioural intention ($r=0.602$, $p<0.001$), indicating facilitating conditions are critical for forming intentions. Moderate to weak correlations with other factors, suggesting its influence is more direct on behaviour than mediated by other variables.

6. **Behavioural Intention vs. Other Factors**

Strong correlations with facilitating conditions ($r=0.695$, $p<0.001$) and Social Factors ($r=0.589$, $p<0.001$) suggest these are primary drivers of intention.

Moderate correlations with Effort Expectancy (0.418, $p<0.001$), Performance Expectancy ($r=0.408$, $p<0.001$), and General Awareness ($r=0.440$, $p<0.001$) indicate these also contribute to intentions but to a lesser extent.

4.7 RELIABILITY

4.7.1 Cronbach Alpha

The reliability of the research instrument was assessed using the Cronbach Alpha test. The Cronbach Alpha method is widely used when determining reliability. The values from a Cronbach Alpha test range from 0 (zero) to 1 (one) where the value closer to 1 suggests a higher reliability. The Cronbach Alpha value of 0.7 or higher is regarded ‘acceptable’ to ‘excellent’ and a value lower than 0.7 is ‘questionable’ to ‘unacceptable’. More detail of the Cronbach Alpha result is shown in the table below.

Table 21 Reliability Analysis: Cronbach Alpha

Constructs	**Number of items**	**Cronbach’s α**	**Reliability level**
General awareness, attitude and trust	10	0.888	Good

Performance expectancy	6	0.930	Excellent
Effort expectancy	6	0.857	Good
Social factors	7	0.870	Good
Facilitating conditions	5	0.841	Good
Behavioural intention	3	0.768	Acceptable

4.8 REGRESSION ANALYSIS

Regression analysis is a statistical technique applied to data to examine the relationships between variables (i.e., the relationship between a dependent variable and one or many independent variables). This technique is widely used in research and is extensively applied to initiatives involving data analytics. A regression analysis was performed to test the research objective 1 (To identify the extent to which the constructs (i.e., general awareness, attitude and trust, performance expectancy, effort expectancy, social factors, facilitating conditions) of the extended UTAUT model influence the intention to adopt intelligent applications in Telecom X. The regression analysis on the dataset collected from respondents examined the relationships between the dependent variable and the numerous independent variables. Regression analysis is widely used in making predictions and highlighting potential causal relationships.

The regression analysis concluded that the general awareness, attitude and trust is a significant and positive predictor. For every unit fluctuation in general awareness, attitude and trust causes the behavioural intention variable to fluctuate by 0.4623 units. The social influence variable is a positive predictor and strongly influences behavioural intention causing a 0.1716 fluctuation in behavioural intention for every unit fluctuation in social influence. The most significant and impactful predictor of all other extended UTAUT constructs on behavioural intention is facilitating conditions. A unit increase in facilitating conditions leads to a 0.4179 unit increase in behavioural intention, highlighting its critical role in this analysis.

The multiple regression equation is used for predicting the behavioural intention (Y) based on the numerous predictors (independent variables) and is expressed as follows:

Equation:

Y (behavioural intention) = β0 + β1 * (general awareness, attitude and trust) + β2 * (attitude and trust) + β3 * (performance expectancy) + β4 * (effort expectancy) + β5 * (social influence) + β6 * (facilitating conditions) + ϵ

Where,

β0 = Intercept term (constant).
β1 – β6 = coefficients representing the impact of each independent variable on behavioural intention.
ϵ = Error term capturing unexplained variability.

Table 22 Model Coefficients - Behavioural Intention

Predictor	Unstandardised Coefficients		t	Sig.(p)	Standardised	Collinearity Statistics	
	Interaction Term (B)	Std. Error			Interaction Term (β)	VIF	Tolerance
Intercept	0.3026	0.3527	0.85799	0.392			
General awareness, attitude and trust	0.4623	0.1078	4.28914	<.001	0.3619	2.09	0.477
Performance expectancy	-0.0861	0.1183	-0.72815	0.468	-0.0785	3.42	0.292
Effort expectancy	2.65e-4	0.1169	0.00227	0.998	2.19e-4	2.76	0.362
Social influence	0.1716	0.0958	1.79088	0.075	0.1584	2.3	0.434
Facilitating conditions	0.4179	0.0716	5.83596	<.001	0.4226	1.54	0.648

Note: [a] Represents reference level

By substituting the values from table 21 the equation is expressed as follows:

behavioural intention (Y) = 0.3026 + (0.4623 × General Awareness, Attitude and Trust) + (-0.0861 × Performance Expectancy) + (0.000265 × Effort Expectancy) + (0.1716 × Social Factors) + (0.4179 × facilitating conditions) + Error term

The Collinearity test was conducted to determine if a strong correlation exists between the independent variables of the regression model. This is measured using the variance inflation factor (VIF). Achieving a VIF value of close to or equal to 1 (no multicollinearity) is the ideal outcome. Table 21 shows the results of the Collinearity test where all independent variables were below the multicollinearity threshold (VIF>10) and tolerance values are above 0.1, therefore all independent variables are regarded as reliable predictors of behavioural intention having a moderate variance inflation factor.

Model Coefficients

The coefficients of the individual predictors provide insight into the potential impact of each construct on behavioural intention.

General awareness, attitude, and trust has a significant positive predictor ($p<0.001$; standardised interaction term = 0.3619), for every unit increase in this independent variable causes behavioural intention to increase by 0.4623 units. This shows the importance of the variable in driving behavioural intention.

Performance expectancy is not a significant negative predictor ($p=0.468$; Standardised Interaction Term = -0.0785).

Effort expectancy is not a significant predictor ($p = 0.998$; standardised interaction term = -0.000219). This suggests that the perceived effort required has little to no impact on behavioural intention in this model.

Social influence is a significant positive predictor ($p=0.075$; standardised interaction term = 0.1584). Social influences strongly impact on behavioural intention, with a unit increase in this variable potentially leading to a 0.1716 unit increase in behavioural intention.

Facilitating conditions is the most significant and impactful predictor of the extended UTAUT constructs ($p<0.001$; standardised interaction term = 0.4226). A unit increase in facilitating conditions leads to a 0.4179-unit increase in behavioural intention, highlighting its critical role.

Normality Test (Shapiro-Wilk)

The Shapiro-Wilk test is widely used to determine whether a dataset follows a normal distribution pattern. The statistical range is between 0 and 1 where the result should be closer to 1, which indicates strong normality.

The p-value will determine where the null hypothesis should be rejected. Significant deviation from normality is usually identified by a $p<0.05$.

Table 23 shows the results of the test where the combination of the statistical value is closer to 1 (0.985) and the p-value is higher than 0.05 (0.094), therefore the dataset conforms to normality.

Table 23 Shapiro-Wilk Normality Test

Statistic	p
0.985	0.094

4.9 MODERATED REGRESSION ANALYSIS

A moderated regression analysis was performed to examine the effect an outlier variable has on the relation between a dependent variable and an independent variable. The outlier variable is known as the moderator and the predictor variables are the constructs of the extended UTAUT model. Behavioural intention is the dependent variable in each hypothesis examined in the section.

The multiple regression analysis was performed to test hypotheses H2, H3, H4, H5, H6, and H7. This technique was used to understand the relationship between the variables and control of the process through potentially new observations.

H2: The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by age.

The coefficients of the individual predictors provide insight into the potential impact of each factor on the behavioural intention. The interactions between age and each predictor are tested to determine if age moderates the relationship between the predictors and behavioural intention. The interaction effect between age and the predictors shows non-significant effects.

The interaction of age ✻ social influence shows one significant result for the 41–50 age group (p=0.014). The findings suggests that the impact of "social influence" on the outcome variable is influenced by age. Specifically, the age group 41–50. Therefore, the hypothesis is partially rejected.

H3: The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by gender.

For hypothesis H3, the details of the coefficient analysis between gender and each predictor are tested to determine if the gender moderated the relationship between the predictors and behavioural intention.

Most of the interactions (i.e., gender ✻ general awareness, attitude, and trust; gender ✻ effort expectancy; gender ✻ facilitating conditions) are not statistically significant (p>0.05). The remaining interactions (i.e., gender ✻ performance expectancy; gender ✻ social factors) show marginal significance of p=0.057 and p=0.089 respectively, suggesting that gender could potentially influence behavioural intention.

Therefore, the hypothesis (H3) is partially rejected.

H4: The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by the level of education.

For hypothesis H4, the details of the coefficient analysis between the level of education and each predictor are tested to determine if the level of education of respondents moderate the relationship between the predictors and behavioural intention.

The main effects of education level on behavioural intention are non-significant ($p > 0.05$). None of the interactions between education and extended UTAUT constructs are statistically significant ($p > 0.05$). Therefore, the level of education does not moderate the relationship between the constructs and the behavioural intention, as none of the interaction effects are statistically significant. The hypothesis (H4) is rejected.

H5: The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by job classification.

Hypothesis H5 proposes that the relationship between behavioural intention and extended UTAUT constructs is significantly influenced by job classification (management vs. non-management roles).

The direct effect of job classification on behavioural intention is not significant ($p = 0.973$). None of the interaction effects between job classification and extended UTAUT constructs are statistically significant ($p > 0.05$). Therefore, the job classification construct does not moderate the relationship between the constructs and the behavioural intention as none of the interaction effects are statistically significant. The hypothesis (H5) is rejected.

H6: The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by the employment contract type.

Hypothesis H6 proposes that the relationship between behavioural intention and all the extended UTAUT constructs is significantly influenced by the employment contract type.

The direct effect of job classification on behavioural intention is not significant ($p = 0.854$). None of the interaction effects between job classification and extended UTAUT constructs are statistically significant ($p<0.05$). Therefore, the job classification does not moderate the relationship between the constructs and the behavioural intention as none of the interaction effects are statistically significant. The hypothesis (H6) is rejected.

H7: The relationship between behavioural intention and all the UTUAT constructs is significantly influenced by the amount of work experience.

Hypothesis H7 proposes that the relationship between behavioural intention and all the extended UTAUT constructs is significantly influenced by years of work experience. From the analysis, we see that several coefficients related to work experience levels, particularly for general awareness, attitude and trust (6–10 years, 16–20 years, more than 20 years) and performance expectancy (6–10 years, 11–15 years, 16–20 years, more than 20 years), show statistically significant results. These findings indicate that work experience does have a moderating influence on the relationship between some of the UTUAT constructs and behavioural intention. Therefore, the hypothesis (H7) is accepted.

Table 24 below shows the summarised moderated regression analysis. The statistics show the relationship between the extended UTAUT predictor and behavioural intention. The table also shows the impact of moderator variables on those relationships.

Table 24 Moderated Regression Analysis

	Behavioural Intention													
	Full Moderated Regression Model		Age		Gender		Education		Job Classification		Employment Contract Type		Experience	
	Beta	**T**	**Coefficient**	**T**	**Coefficient**	**T**	**Coefficient**	**T**	**Coefficient**	**T**	**Coefficient**	**T**	**Coefficient**	**T**
General awareness, attitude and trust	0.3619	4.28914	0.1421	0.343	0.37136	1.7016	0.4312	1.2751	0.4873	3.5109	0.2083	1.350	3.43724	2.50895
Performance expectancy	-0.0785	-0.72815	-0.1119	-0.244	0.21834	1.1020	-0.8284	-0.7789	-0.0560	-0.3620	0.0691	0.440	-2.92470	-2.37048
Effort expectancy	2.19e-4	0.00227	0.2602	0.755	-0.01146	-0.0620	-0.1472	-0.1701	-0.1055	-0.6442	0.0871	0.645	-0.67546	-0.80537
Social factors	0.1584	1.79088	-0.3395	-1.074	-0.00227	-0.0155	0.8258	1.0959	0.2647	1.8831	0.2868	2.584	0.78769	1.59050
Facilitating conditions	0.4226	5.83596	0.4168	2.143	0.34705	2.8806	0.4977	0.8903	0.3700	3.7071	0.3428	4.234	-0.07128	-0.12586
R^2	0.487													

**p<0.01; *p<0.05

4.10 TEXT ANALYSIS

The final two questions on the survey asked respondents in the support services to express their views on potential barriers and enablers to adopting the use of intelligent applications in their respective job functions. The respondents were able to use the free form text fields to express their perspectives. The researcher analysed the text using a thematic analysis technique performed manually in Microsoft Excel. The steps involved in conducting a thematic analysis are as follows:

1. **Data familiarity:** This step involves the researcher reading the content of the responses to gain better familiarity.
2. **Generate initial codes:** Initial terms and words are identified and applied to filter responses. The words and terms mentioned most frequently in responses were used as the primary criteria.
3. **Search for themes:** The results of the code filtration were reviewed and grouped into themes.
4. **Review themes:** The themes were reviewed together with responses to determine context and potential sub-themes.
5. **Define and name themes:** The themes were labelled.
6. **Compile the write-up:** The study combines the learnings of the preceding steps into a narrative.

During the thematic analysis process the researcher excluded ‘stop words’. The outcomes of the thematic analysis are shown in the tables below.

4.10.1 Barriers to the adoption of Intelligent Applications in Telecom X

The results of the thematic analysis highlighting the barriers for adopting intelligent applications in an ICT company are shown in table 25.

Table 25 Barriers to the adoption of intelligent applications

Rank	Keyword	Frequency
1	* Training	22
2	*** Support	20
3	** Data	20
4	*** Time	19

5	* Skills	19
6	* Knowledge	18
7	Management	17
8	Cost	18
9	**** Change	15
10	** Security	12
11	Systems	11
12	**** Resistance	10
13	Learning	10
14	Funds	9
15	Budget	8

The most frequently mentioned barrier to adopting intelligent applications in Telecom X is **'training.'** The sub-themes identified within the training barrier focuses on the strong need for training programmes to upskill and reskill respondents and potentially encourage employees to adopt the use of intelligent applications.

'Data' plays a key role in the successful implementation and maintenance of intelligent applications and includes sub-themes such as data security, access to data, data quality and data management. These items focus on the integrity and availability of data needed to drive the benefits of using intelligent applications to perform business functions.

'Management support' for the adoption of intelligent applications was ranked third and includes on-the-job support when using intelligent applications to accomplish business functions.

'Financial constraints' represent a significant barrier to adoption, emphasising the challenges organisations face in securing adequate budgets for both implementation and ongoing maintenance of new digital technologies like intelligent applications. Notably, financial concerns frequently co-occurred with training-related and support-related challenges, indicating a direct relationship between budget limitations and the ability to upskill and support employees effectively.

Introducing new technologies could potentially have an impact on processes (ways of work), which will require change management initiatives to improve adoption.

Responses included several instances citing ‘resistance to change’ as a barrier to the adoption of intelligent applications in Telecom X.

Though the code words are shown in the table in descending order of frequency, the following themes have emerged:

Table 26 Barrier Themes

Themes
* Knowledge, skills, and training
** Data, security, privacy
*** Support, time, strategy
**** Financial impact (budget/funds/cost/finance)
***** Change management, resistance to change

4.10.2 Enablers to the adoption of Intelligent Applications in Telecom X

The results of the thematic analysis highlighting the enablers for adopting intelligent applications in an ICT company are shown in table 27.

Table 27 Enabler to the adoption of intelligent applications

Rank	Keyword	Frequency
1	* Time	25
2	* Use	21
3	** Training	21
4	** Support	21
5	*** Improve	16
6	*** Efficiency	16
7	Application	16
8	Intelligent	15
9	Work	14
10	*** Customer	14
11	Task	13
12	Access	12

13	Reduce	11
14	* Productivity	10
15	Availability	9

The most frequently mentioned is time. The respondents expand in several contexts on the reduction of time wasted on business functions. This impacts the volume and quality of business deliverables by reducing time wasted on monotonous and manual tasks. The integration of intelligent applications into current business functions could potentially result in higher productivity and time savings.

The ease of use of intelligent applications contributes to the adoption when the technology is integrated into the business function. Support from management is needed to drive the adoption of intelligent application.

Training is required to increase awareness of intelligent applications. Knowledge and skills to use intelligent application will also increase. To accomplish this, management support in terms of strategy and execution is needed.

Organisational structures to support the users that make use of intelligent applications is needed to ensure that the most value extraction and productivity are achieved.

Though the code words are shown in the table in descending order of frequency, the following themes have emerged:

Table 28 Enabler Themes

Enabler Themes
* Increase productivity (time, use, productivity, work)
** Training (training, support, development)
*** Customer experience (improve, efficiency, customer, availability)

CHAPTER 5: DISCUSSION OF THE FINDINGS

5.1 INTRODUCTION

This chapter presents a summarised interpretation of the research findings. The findings are analysed in relation to the objectives of this study. The aim of the research study was to examine the factors that influence the adoption of intelligent applications in Telecom X.

5.2 SUMMARY OF THE STUDY

The emergence of digital technologies has altered how organisations operate. According to the Digital Vortex 2023 Report, 64% of global businesses claimed to be aware of digital technologies but were uncertain about how to respond to this wave of transformation events to prepare themselves or were uncertain how to respond. Hybrid industries have emerged where organisations diversify their business models to operate in multiple industries according to Wade et al. (2023). For other organisations, the benefits of digital transformation initiatives have been integrated into their business operations to remain competitive amidst digital technology disruption according to Högberg and Willermark (2022). As technology continues to evolve, simply digitalising business operations may not be sufficient in maintaining relevance. The integration of disruptive digital technologies, like intelligent applications, could potentially determine an organisation's survival. The sharp increase in the number of artificial intelligence enabled applications that support organisations across various sectors has increased. The advancements in IT infrastructure have driven demand for more computing power in support of data-driven initiatives (Hernandez, 2024). The wave of disruption has spilled over into organisations who face the challenge of servicing customers who are more technology savvy. This has led to changing customer needs that influence the expectations that customers have of organisations. These changes have fuelled the demand for intelligent applications, which integrate AI techniques from various data sources to improve customer experience (Wiles, 2023). Many South Africa organisations have begun implementing AI tools (i.e., intelligent applications) to perform various operational functions. These organisations are at different stages of digital maturity and at different points in the adoption journey (Schoeman & Seymour, 2022).

This study examined the factors that influence the adoption of intelligent applications in Telecom X by extending the UTAUT model (Venkatesh et al., 2003). The extension included additional independent variables such as level of education, job classification, employment contract type to the traditional independent variables (i.e., age, gender, experience). The goal was to determine which of these factors would significantly influence the adoption of intelligent applications in Telecom X and the extent to which these factors have an influence. This research approach and model were selected to gather insights from a South African ICT perspective. This research will contribute to the existing body of knowledge on technology adoption within the South African ICT context.

The study's objectives were to:

- identify the extent to which the constructs of the extended UTAUT model (Venkatesh et al., 2003) influence the intention to adopt intelligent applications in Telecom X;
- determine how demographic factors (i.e., business unit, age, gender, experience, level of education, job classification and employment contract type) influence the constructs of the extended UTAUT model and affect employee intention to adopt intelligent applications;
- identify potential barriers to the adoption of intelligent applications in the organisation; and
- identify potential enablers for the adoption of intelligent applications by employees in the organisation.

The research employed a quantitative research approach, targeting employees in a customer support role or those managing customer support teams. The population also included employees who have had prior experience in customer support. The term "customer" in this context refers to both "external clients" (i.e., people who buy products or service users) and "internal clients" (i.e., other departments within the organisation requiring services). The study used a non-probability sampling method, incorporating purposive, convenient and snowball sampling methods as recommended by Greener (2008). The purposeful selection of participants was aimed at meeting the study's objectives. The total of 160 participants completed the survey.

The online survey was created and structured using Qualtrics, web-based software application. The data was exported for analysis using Jamovi statistical analysis software. The open-ended responses were analysed with a Word Cloud online application and analysed in Microsoft Excel.

A high-level analysis of the data revealed that most respondents were aged between 31–60 years, with the largest group (31.9%) falling within the 41–50 age range. The gender contribution was nearly equal, with male respondents accounting for 50% and female respondents accounting for 49.4%. Respondents who had obtained formal qualifications were 88.8%. The job classification variable was roughly evenly split between management (53.8%) and non-management (46.3%). The employment contract types show that permanent employees contribute 78.1%, and contractors contribute 21.9% of the sample. The spread of work experience concentrated with the 2–5 and 6–10 year ranges.

Research Objective 1: To identify the extent to which the constructs of the extended UTAUT model influence the intention to adopt intelligent applications in Telecom X.

This research objective utilised the extended UTAUT model to assess how constructs such as general awareness, attitude and trust, performance expectancy, effort expectancy, social influence and facilitating conditions have an impact on employees' behavioural intention to adopt intelligent applications (Venkatesh et al., 2003). Numerous research articles support the influence of these constructs on the behavioural intention to adopt new technology like Alshrouf et al. (2024) and Wongras and Tanantong (2023).

The study's hypothesis (H1) states that the predictors of the extended UTAUT model significantly and positively influences the intention to adopt intelligent applications.

The results of the regression analysis indicated that general awareness, attitude and trust and facilitating conditions were the strongest positive predictors of adoption. Increased general awareness, attitude, and trust significantly enhance respondents' belief that such tools could complement their job functions, especially in customer service roles. Respondents also perceived intelligent applications as capable of automating routine tasks, resulting in dependable and efficient outcomes according to Akoh (2024) and Rizkalla et al. (2024).

Facilitating conditions, the second strongest predictor, also significantly influence the adoption of intelligent applications. This suggests that better facilitating conditions (i.e., robust IT infrastructure, support resources and support systems) considerably and positively influence the adoption of intelligent applications. Employees felt strongly that there need to be organisational structures to support the learning and use of intelligent applications as highlighted by Akoh (2024).

Social influence is indicated as having a moderate and statistically weak influence on the adoption of intelligent applications. Analysis from a higher number of respondents could potentially reveal greater insights into this construct as suggested in Budhwar et al. (2022).

In contrast, the result of the regression analysis revealed that performance expectancy and effort expectancy are not significant predictors of behavioural intent. This could be attributed to respondents' confidence in the effectiveness of intelligent applications, as well as concerns over the potential increase in effort required for their use. These findings align with other research in this area shown by Rizkalla et al. (2024) and Saravanos et al. (2022).

To summarise, general awareness, attitude and trust, and facilitating conditions have a positive and significant influence on adoption. Performance expectancy and effort expectancy have proven not to have a positive influence. The social influence demonstrates a moderate influence on the behavioural intention. Further research in this regard is recommended.

Research Objective 2: To determine how demographic factors (i.e., age, gender, experience, level of education, job classification, and employment contract type) influence the constructs of the extended UTAUT model and affect employee intention to adopt intelligent applications.

This objective explored how demographic variables (i.e., age, gender, level of education, job classification, employment contract type and work experience) influence the adoption of intelligent applications. The analysis aimed to provide deeper insights into how these factors moderate the relationship between the extended UTAUT constructs and the adoption original model by Venkatesh et al. (2003).

The research objectives applicable to this study are:

The hypotheses (H2-H7) states that demographic factors would significantly influence the relationship between the UTAUT constructs and behavioural intention.

The following hypotheses are applicable to research objective 2:

- **H2:** The relationship between behavioural intention and the predictors of the extended UTUAT model is significantly influenced by age.
- **H3:** The relationship between behavioural intention and the predictors of the extended UTUAT model is significantly influenced by gender.
- **H4:** The relationship between behavioural intention and the predictors of the extended UTUAT model is significantly influenced by the level of education.
- **H5:** The relationship between behavioural intention and the predictors of the extended UTUAT model is significantly influenced by job classification.
- **H6:** The relationship between behavioural intention and the predictors of the extended UTUAT model is significantly influenced by the employment contract type.
- **H7:** The relationship between behavioural intention and the predictors of the extended UTUAT model is significantly influenced by the amount of work experience.

The results revealed that gender, level of education, job classification, and employment contract type have no material influence on the adoption of intelligent applications. Similarly, there is no significant influence of age on adoption.

The results confirm that there is a relationship between social influence and behavioural intention. While most age-related interactions do not significantly influence adoption, the relationship between social influence and behavioural intention is significantly influenced by the 41–50 age group. Therefore, the results partially support hypothesis H2c (The relationship between behavioural intention and the social influence is significantly influenced by age) aligned to the study by Akoh (2024).

In addition, the analysis suggests that the relationship between behavioural intention and several UTUAT constructs is significantly influenced by the amount of work experience. General awareness, attitude and trust (i.e., 6–10 years, 16–20 years and more than 20 years) and performance expectancy (i.e., 6–10 years, 11–15 years, 16–20 years and more than 20 years) have a significant and positive influence on behavioural intention. These findings indicate that work experience does moderate the relationship between some of the extended UTUAT constructs and behavioural intention according to the study by Rizkalla et al. (2024). Therefore, hypothesis H7a (relationship between behavioural intention and the general awareness, attitude and trust is significantly influenced by the amount of work experience) and H7b (relationship between behavioural intention and the performance expectancy is significantly influenced by the amount of work experience) are supported by the research.

The remaining sub-hypothesis for this research study was rejected. The results of this research study were partially aligned to the literature survey where the moderating variables influence the relationship between behavioural intention and the constructs of the UTAUT model by Venkatesh et al. (2003). A potential reason for the misalignment could be explained by the sample size. This research study was purposive, focusing on specific business functions within the organisation, which may have influenced the outcome of the study. Other contributing factors could potentially be that the study focused on a single ICT organisation. Adding other ICT organisations to the study could have provided holistic insight into new technology adoption since each execute different strategies.

Research Objective 3: To uncover potential barriers for the use of intelligent applications by employees of Telecom X.

This section of the study focuses on the responses to an open-ended question posed during the survey to allow respondents to provide insights about potential barriers to the adoption of intelligent applications. Several topics (i.e., training, data, management support, and financial constraints) emerged as the most significant obstacles.

Training was identified as the greatest obstacle. This topic contains several sub-topics revealing the need for training programmes to upskill employees into using intelligent applications, potentially leading to improved job performance. Regular training programmes help to reskill employees, which lead to improved adoption behaviour in an era when repetitive tasks are absorbed by automation suggested in the study Akoh, (2024).

The second most impactful obstacle identified by the analysis was data and included sub-topics such as data quality, data security, and data management. This topic is of particular concern since intelligent applications require high quality data for effective and accurate decision making. The data management controls are crucial for maintaining an acceptable data quality standard and ensuring the data is stored in a secure environment and is void of exposure as mandated by regulations concerning data privacy and data protection according to the study by Schoeman and Seymour (2022).

Management support was ranked third and contains sub-topics that focus on employee support for the use of intelligent applications. This includes on-the-job support while executing tasks. The implementation of effective change management was also a key sub-topic when transitioning from old technology and processes to new technologies and ways of work aligned with other studies Kunene, (2023 and Thakur et al., (2022).

Financial constraints represent a significant barrier to the adoption of intelligent applications. The topic emphasises the challenges most organisations encounter when securing investments for implementation and maintenance of intelligent applications revealed in a study by Schoeman and Seymour (2022).

In summary, these obstacles relate to the UTAUT construct of facilitating conditions that have a significant influence on the adoption of intelligent applications. The results of the analysis share similarities with other studies on the topic of new technology adoption in other industries. The study provides insights and recommendations to organisational leadership to factor into the planning and implementation of intelligent applications.

Research Objective 4: To highlight potential enablers for the use of intelligent applications by employees of Telecom X in performing their respective business functions.

Respondents also highlighted enablers that could facilitate adoption. The thematic analysis revealed the emergence of several topics (i.e., time savings, improved productivity, training, and customer experience). The outcomes from the thematic analysis align with the outcomes of the statistical analysis.

Time was the most frequently cited enabler, with respondents recognising that intelligent applications could reduce time spent on repetitive tasks, enabling employees to focus on delivering higher-quality outputs aligned to the study Patel (2024).

Training emerged as a critical enabler to raise awareness through upskilling employees. Success is all but guaranteed by integrating intelligent application into employee's job functions. This topic was also highlighted as a barrier to adoption emphasising the roles of training in technology adoption according to the study by Akoh (2024).

Increased levels of customer experience are achieved by integrating intelligent applications into the employees' job functions and the self-service function exposed to customers, hence increasing the focus on customer centricity according to Thakur et al. (2022).

5.3 CONCLUSION TO FINDINGS AND RESULTS

This study offers valuable insights into the factors influencing the adoption of intelligent applications within Telecom X. By extending the UTAUT model, the research identifies key predictors of adoption, including general awareness, attitude, trust, and facilitating conditions. These findings reaffirm the necessity for fostering organisational awareness and trust in intelligent technologies while ensuring robust infrastructure and support mechanisms.

Work experience emerged as a significant moderating factor, influencing behavioural intentions. Although demographic variables had minimal impact, barriers such as training deficiencies, data concerns, management support, and financial limitations were significant obstacles to adoption. This observation suggests that practical exposure and familiarity with operational processes may enhance an individual's ability to appreciate the value proposition of intelligent technologies.

Barriers to adoption were identified, with training deficits, concerns about data quality and management, limited management support, and financial constraints emerging as significant challenges. Overcoming such barriers is crucial to fostering the effective and sustainable adoption of new technologies. Conversely, the study highlighted several enablers, including time efficiency, enhanced customer experiences, and structured training interventions, which can facilitate seamless technology integration into business functions.

In conclusion, this study contributes to the body of knowledge on technology adoption within ICT environments by elucidating the complex interplay of factors that influence employee adoption of intelligent applications. The findings suggest that organisations should invest in targeted training programmes, data management frameworks, and strategic leadership initiatives to overcome barriers and optimise the benefits of intelligent applications. Further research is recommended to explore these findings across a broader range of industries and organisational contexts to build a more holistic understanding of technology adoption dynamics.

CHAPTER 6: RECOMMENDATIONS, LIMITATIONS AND FUTURE RESEARCH

This chapter provides an overview of the key findings of the study. This includes recommendations based on the analysis of data collected from respondents and supported by the contemporary literature surveys.

6.1 RECOMMENDATIONS

The results presented in the study draw attention to the most significant constructs of the UTAUT model and the factors that influence the adoption of intelligent applications in Telecom X. The statistical analysis of the data combined with the thematic analysis reveal key patterns that align with existing literature on technology adoption, particularly the integration of AI-driven applications in organisational settings by Venkatesh et al. (2003). Respondents expressed their familiarity with AI tools and the value such tools could present when integrated with their job functions. Using intelligent applications could reduce repetitive tasks and outperform manual activities. Therefore, general awareness and attitude and trust had emerged as the strongest determinants of behavioural intention. The second strongest influence on behavioural intention was facilitating conditions. These conditions include the element that make up the environment surrounding the respondents and include infrastructure, systems, processes and procedures, organisational support, and training programmes. These findings are consistent with existing models of technology adoption, which highlight the importance of both individual perceptions and environmental factors aligned with studies by Alshrouf et al. (2024) and Wiles (2023).

Based on these insights, organisations should focus on enhancing general awareness and cultivating trust in intelligent applications. Additionally, they must ensure robust facilitating conditions particularly regarding infrastructure, system integration, and adequate training to optimise the adoption process.

6.2 MANAGEMENT SUPPORT AND STRATEGY

Digital transformation has become a growing part of the consumer market, reshaping the way we think, act and reason in constantly changing circumstances. Over the recent years this transformation has had an impact on employees' nature of work and imposed changes to business strategies and models. These changes were greatly accelerated because of the COVID-19 pandemic that had an impact on lifestyles and organisations globally. This event increased the rate of adoption of digital technologies and the diffusion of these technologies into organisations to remain competitive as mentioned by Poisat et al. (2024).

It is essential for the leadership in organisations to plan and implement effective change management initiatives to support employees and the greater organisational functions to prepare for the future dominated by AI. The assimilation of AI techniques merged with applications is gaining momentum. Typical examples include the WhatsApp Messenger application that now contains Meta AI and Microsoft Copilot being integrated into the word processor (Microsoft Word) and spreadsheet (Microsoft Excel) applications to name a few. Technology companies in South Africa are developing applications integrated with AI technology to support customer needs as featured in an article by Burrows (2024).

The example of Blockbuster can be used as a case study for digital disruption where Blockbuster was a leading video rental chain known for its extensive network of physical stores. The company failed to recognise the shift towards digital streaming and declined opportunities to partner with emerging platforms like Netflix. This reluctance to embrace new technology led to its bankruptcy in 2010 according to the case study by Krishna (2018).

This topic highlights the importance of formulating new business strategies by embracing digital technologies, like intelligent applications, to ensure the survival of the organisation according to Högberg and Willermark (2022). There are several instances where organisations were impacted by the digital transformation crises and did not recover. On the other hand, there were situations where organisations in similar predicaments, through strategy re-alignment and technology changes, were able to recover and succeed according to the study by Van Der Zwan (2023).

6.3 TRAINING AND IT INFRASTRUCTURE

This topic is largely dependent on the establishment of a business strategy to adopt digital technologies. A critical part of a change management strategy is to ensure effective communication (enhancing general awareness, shaping employee attitudes and building trust) before, during and after the change process. This ensures the transparency through the change initiatives and prevents employees from panic causing resistance to change initiatives according to Jeza and Lekhanya (2022). The use of intelligent applications aids in helping organisations cope in a volatile marketplace.

Organisations need to better understand the value that intelligent applications can deliver and leverage these capabilities in coping with the increasing changes to customer needs. This is accomplished by strengthening the facilitating conditions to support the implementation of intelligent applications. It is worth noting that according to Venkatesh et al. (2003) in the UTAUT model, facilitating conditions have a direct impact on usage behaviour meaning that even though employees' perception of the technology is positive, their usage behaviour can be low if the technology is difficult to use. Ensuring that the IT technical infrastructure is stable and robust to enable the smooth operation of intelligent applications is crucial. The systems implemented should be compatible and integrated to intelligent applications to avoid that employees perform manual and repetitive tasks. Having the necessary resources to provide on-job-support to ensure that productivity is maximised, and process waste is kept to a minimum. Finally, training programmes are needed to upskill employees adopting intelligent applications into their current functions and to reskill employees who are occupying roles that will change completely as conveyed by Schoeman and Seymour (2022).

6.4 DATA MANAGEMENT

The topic on data management was highlighted by respondents as being a barrier to adopting intelligent applications. The sub-topics included are data security, data privacy, and data quality. The quality of data consumed by intelligent applications could potentially negatively impact the effectiveness of results produced. It is therefore crucial for the organisation to ensure that effective data governance and data management controls are implemented and maintained to ensure the highest level of data quality. The data management controls extend to data security and data privacy to ensure that data is stored in a safe and secure location and protected from unauthorised breaches. With growing applications for data- driven decision-making technologies like intelligent applications, it is essential that organisational and customer data be classified as an organisational asset. This aligns with the research articles regarding challenges when adopting new technology (Schoeman & Seymour, 2022).

6.5 ADDITIONAL RECOMMENDATIONS:

Other recommendations that stem from the statistical analysis are:

1. **Adopt intelligent applications**: Organisations should focus on embracing intelligent applications to strengthen their digital presence and enhance customer engagement. These applications provide valuable insights into customer behaviour and market trends, enabling businesses to remain competitive by adapting to emerging shifts in the market.
2. **Leverage digital technologies**: Integrating technologies such as RPA and AI into existing business processes can optimise operational performance. These technologies can drive innovation, improve efficiency, and support new business models, helping businesses to enhance their operational effectiveness.
3. **Prioritise the customer experience**: Organisations should make the digital customer experience a top priority. Leveraging intelligent applications can provide deeper insights into customer preferences and needs, resulting in better service delivery, improved interactions, and increased customer satisfaction.
4. **Invest in change management**: The adoption of intelligent applications requires change management strategies. Organisations must ensure that employees receive appropriate training and ongoing support to ease the transition and ensure smooth and sustained implementation.
5. **Overcome potential barriers**: Organisations should tackle barriers to adoption, such as resistance to change, skills gaps, and data security concerns. Early identification of these barriers and strategies to overcome them will smooth the path to integration and increase adoption rates.
6. **Highlight enablers for adoption**: The successful adoption of intelligent applications relies on key enablers. Strong leadership support, clear communication of benefits, and alignment with broader business objectives are critical factors for successful adoption and integration. Organisations should ensure these elements are in place to facilitate effective implementation.

7. **Enhance general awareness, attitude, and trust**: Given the positive influence of general awareness, attitude and trust on behavioural intention, organisations should prioritise initiatives such as awareness campaigns, transparent communication, and trust-building strategies. These efforts can foster a positive attitude and increase trust in the new technology, thereby driving adoption.
8. **Focus on facilitating conditions**: Organisations should invest in the necessary infrastructure, resources, and support systems to ensure easy adoption. This includes providing user-friendly interfaces, robust technical support, and removing logistical barriers that could hinder the adoption process.
9. **Simplify effort expectancy**: Even though effort expectancy has a minimal impact, organisations should still simplify the adoption process. Streamlining user interfaces, offering clear instructions, and providing ongoing support will make the technology adoption smoother and more accessible.
10. **Optimise time management**: Given the frequency of time-related enablers, organisations should focus on optimising time management during the adoption process. This includes setting clear timelines, streamlining the implementation process, and ensuring efficient allocation of resources to avoid delays.
11. **Ensure ease of use and access**: Organisations should ensure that intelligent applications are user-friendly and easy to integrate into existing systems. Simplifying the onboarding process and providing intuitive interfaces will enhance accessibility and facilitate smoother adoption.
12. **Invest in training and support**: Organisations should place emphasis on comprehensive training programmes and continuous support to equip employees with the necessary skills to utilise intelligent applications effectively. Ongoing mentorship and support channels, such as helpdesks, will also assist in smooth transitions.
13. **Focus on improving efficiency and productivity**: Demonstrating how intelligent applications enhance efficiency and productivity is crucial. Organisations should showcase the practical benefits of adopting these applications through case studies, pilot projects, and clear communication about timesaving and productivity-enhancing features.
14. **Enhance customer interaction**: Organisations should focus on integrating customer-centric features in intelligent applications. By automating responses,

personalising interactions, and improving support services, organisations can enhance overall customer satisfaction.

15. **Adopt a task-specific approach**: Intelligent applications should be tailored to specific roles and tasks within the organisation. A task-driven approach will ensure that these applications align with user needs and contribute to operational efficiency.
16. **Ensure availability**: Organisations should invest in reliable systems to ensure the consistent availability of intelligent applications. This includes providing robust infrastructure, disaster recovery plans, and regular maintenance to prevent downtime.

6.6 LIMITATIONS OF THE STUDY

This section states the study's identified limitations.

- The study was conducted in a single ICT organisation operating in South Africa. The results accomplished for this industry could be skewed as a result. Access to staff of other organisations was limited during the time of research.
- There is limited research performed in South Africa for this sector. Other similar studies performed in the sector for other organisations could use this research study to benchmark findings.

6.7 RECOMMENDATION FOR FUTURE RESEARCH

This section focuses on recommendations for future studies given the observations and learnings during the execution of this study.

- The moderating variable job classification has no significant influence on the behavioural intention to adopt intelligent applications. Further studies should investigate whether organisational hierarchy, decision-making authority, or specific job functions play a more significant role in moderating behavioural intention than broad job classifications.
- According to the UTAUT model, gender plays a significant role and moderates the relationship between the constructs and the dependent variable (behavioural intention). In this study, the hypothesis was rejected. Further studies should explore qualitative insights to understand why gender does not significantly moderate these relationships.

- The level of education does not significantly influence the relationship between the constructs and the dependent variable (behavioural intention). Further studies could explore whether work experience or industry-specific knowledge plays a greater role in moderating behavioural intention than formal education levels.

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APPENDIX (Research Instrument)

Questionnaire: The use of Intelligent Applications in Customer Services and operational support.

Section A: Participant Details

Business unit:

- ☐ BU-A
- ☐ BU-B
- ☐ BU-C
- ☐ BU-D

Age:

- ☐ 20 or under
- ☐ 21 – 30
- ☐ 31 – 40
- ☐ 41 – 50
- ☐ 51 – 60
- ☐ 61 and above

Gender:

- ☐ Male
- ☐ Female
- ☐ Non-binary / third gender
- ☐ Prefer not to say

Highest Educational Background?

- ☐ Matric
- ☐ Diploma
- ☐ Bachelor’s degree
- ☐ Honours Degree
- ☐ Master’s Degree
- ☐ Doctorate
- ☐ Other

Are you in a Management or non-management position?

- ☐ Management
- ☐ Non-management

Are you a permanent employee or contractor:

- ☐ Permanent Employee
- ☐ Contractor

Please provide the number of years you have worked for the company:

- ☐ 2 – 5 years
- ☐ 6 – 10 years
- ☐ 11 – 15 years
- ☐ 16 – 20 years
- ☐ More than 20 years

How do you characterise your overall understanding of computer programs:

- ☐ Basic
- ☐ Proficient
- ☐ Advanced

How do you rate your knowledge of intelligent applications:

- ☐ Basic
- ☐ Proficient
- ☐ Advanced
- ☐ Not Applicable

How long have you used intelligent applications?

- ☐ Never
- ☐ Sometimes
- ☐ About half the time
- ☐ Most of the time
- ☐ Always

Section B: The section of the questionnaire examines the respondent's attitude, perceived usefulness, effort expectancy, social and facilitating conditions for using intelligent applications in your current job function. The items will be rated using a 5-point Likert scale.

B1	General Awareness, Attitude and Trust between Intelligent Applications and Customer Services	1	2	3	4	5
B1.1	I believe that intelligent applications will provide value when performing my job function.					
B1.2	I like to use an intelligent application when performing my tasks.					
B1.3	I trust the results provided from an intelligent application when performing my tasks.					
B1.4	I feel comfortable working with intelligent applications?					
B1.5	I believe that using intelligent applications to perform my tasks will reduce cost for the company.					
B1.6	Real-time assurance (i.e., customer / end-user support) will be possible with intelligent applications.					
B1.7	In my opinion, intelligent applications will outperform manual activities in delivering dependable outcomes for repetitive jobs and tasks involving the utilisation of numerous intricate systems.					
B1.8	I believe that intelligent applications will be able to provide reliable results that require cognitive functions such as the application of professional judgement when providing feedback to customers.					
B1.9	I believe that intelligent applications will be used to complement the work of customer service agents in the future.					
B1.10	My organisation is currently using or planning to use intelligent applications as part of its strategic goals.					
B2	Performance Expectancy	1	2	3	4	5
B2.1	Intelligent Applications are useful in the customer service environment.					
B2.2	Intelligent application enables customer service agents to accomplish tasks more quickly.					
B2.3	Using intelligent applications in my job will save a significant amount of time.					
B2.4	Using intelligent applications would help me perform better by reducing potential errors.					
B2.5	I will add more value to my work by using intelligent applications.					
B2.6	Having intelligent applications could free up my time so I can work on other projects.					
B3	Effort Expectancy	1	2	3	4	5

B3.1	I enjoy learning about how to leverage the benefits of using various technologies in my job.					
B3.2	I consider intelligent applications is easy to use.					
B3.3	Using intelligent applications reduces the time to upskill / reskill employees.					
B3.4	I have the technical skills needed to use an intelligent application in performing my job functions.					
B3.5	Adopting process changes in customer service is made simpler by the use of intelligent applications.					
B3.6	Using an intelligent application will make my work easier.					
B4	Social Factors	1	2	3	4	5
B4.1	My organisation supports the use of intelligent applications in my job.					
B4.2	Using an intelligent application at work would elevate me to having a higher social status than those who do not.					
B4.3	My friends/family support the use of intelligent applications both socially and professionally.					
B4.4	My manager supports the use of intelligent applications in my job.					
B4.5	Using an intelligent application in my job will advance my career progression (promotions, opportunities, remuneration, etc.).					
B4.6	The teams that I support encourage the use of intelligent applications.					
B4.7	The expectations of my business partners / clients are that support functions should employee the use of intelligent applications.					
B5	Facilitating conditions	1	2	3	4	5
B5.1	My organisation has structures to support learning and understanding the use of intelligent applications.					
B5.2	There are government and country-wide initiatives across South Africa that supports the use of intelligent applications in support services.					
B5.3	My organisation has the necessary funds available for me to learn or use intelligent applications in performing my job function.					
B5.4	My organisation has the necessary skills to start using intelligent applications.					

B5.5	I have access to the relevant support should I need help when problems are encountered while using intelligent applications.					
B6	Behavioural Intention	1	2	3	4	5
B6.1	I intend **using** intelligent applications in performing customer support work in the next 12 months.					
B6.2	I predict that intelligent applications will be used in my organisations for performing customer services in the next 24 months.					
B6.3	I intend **learning** to use intelligent applications in the next 12 months.					

Section C: The section of the questionnaire examines the respondent's perception of the top three barriers and enablers for using intelligent applications in customer service.

C	Barriers and Enablers for Adoption of Intelligent Applications in Customer Services
38	What are 3 barriers that would affect your use of intelligent applications in your career? (3 text boxes with 180-character limit)
39	What are 3 enablers that would increase your use of intelligent applications in your career? (3 text boxes with 180-character limit)

Cover Page:

Good day,

My name is Chiresh Kawal. I am a student in the MMDB (master's degree in management in the field of Digital Business) facilitated by Wits Business School under the supervision of Dr Tebogo Sethibe.

I am conducting a research study that investigates the factors influencing the adoption of intelligent applications by South African organisations. The study aims to investigate which factors influence the use of intelligent applications (i.e., Intelligent applications use historical and real-time data from user interactions and other sources to make predictions and suggestions, delivering personalised and adaptive user experiences.).

The results from this survey will contribute to the existing body of knowledge for this topic from a South African perspective. The research study is completely anonymous (i.e. no personal identification information is required of you). The survey does require that the business unit be identified in addition to the demographic data to align with the Unified Theory of Acceptance and Use of Technology (UTAUT) model.

Please note the following regarding your participation:

- Participation is **voluntary**, and you can withdraw at any time, without any negative consequences.
- **No personal information** is required of you, and this survey is completely **anonymous**.
- By completing this questionnaire, you agree that your **responses can be used in the study**.
- There are **no risks involved in participation**, and you will not be disadvantaged in any way for choosing to participate.
- Completed questionnaires will be **stored in a secure location**. Furthermore, only the researcher and statistician will have access to the **password-protected data**.
- The dataset may be used for **future research**, in which the same **confidentiality and anonymity will be upheld**.
- The results may be used in the **publication of journals and / or conference presentations**.

The questionnaire should take no more than 15 minutes of your time. As your participation is **voluntary** you are not obligated complete the survey, though **completion of the survey is encouraged** to establish usable results for this study.

Should you have any questions or want to be informed of the findings of the study, please feel free to contact:

Chiresh Kawal: 2513888@students.wits.ac.za (Researcher)
Dr Tebogo Sethibe: tebogo.sethibe@wits.ac.za (Supervisor)

Thank you for taking the time to complete this survey.