Gordon Institute of Business Science
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Understanding the readiness of banking industry employees to adopt artificial intelligence in frontier markets

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ABSTRACT

The rate of technological change and its effect on business is occurring at an alarmingly rapid pace. As a result of this, organisations seeking to increase their competitiveness are investing significantly in digital technologies such as artificial intelligence in order to stay relevant. The banking industry has been an early adopter of artificial intelligence.

The banking industry workforce has been subjected to precipitated technological change. This research intended to understand the readiness of the Zambian banking industry employees to adopt artificial intelligence through the investigation of five factors and their impact on AI adoption. These five factors are organisational leadership clarity, employee skill levels, employee attitude to change, cost of implementation and the population's access to technology.

The research study was deductive and quantitative in nature and it was conducted utilising a sample of 365 employees from a named bank in Lusaka, Zambia. The results indicated that while all five factors directly impacted artificial intelligence adoption with varying levels of strength, only organisational leadership clarity and the population's access to internet were significant predictors of artificial intelligence adoption.

The study's findings are of significant importance to organisations that seek to understand their workforce's ability to adapt to the adoption of artificial intelligence.

KEYWORDS

Artificial Intelligence Adoption

Employee Readiness

Frontier Markets

Technological Change

DECLARATION

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

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CHAPTER 1:
BACKGROUND TO THE STUDY

1.1 Context of the study

Technological advances such as artificial intelligence have transformed work globally (Siddhartha & Luc, 2017). Automation, and more recently Artificial Intelligence (A.I.) have contributed to labour displacements as there are increases in productivity and decreases in transactional costs. Human beings have encountered industrial revolutions which can be traced back to the 1800's Luddite Era (Rockstroh & Rotman, 2013). This particular technological revolution has a more ominous tone as there are debates about its labour displacement effect, coupled with the substantial investments in technological advances (Schatsky, Muraskin & Gurumurthy, 2015). Unlike the previous industrial revolutions, the breakthrough speed of this current one is unprecedented. The change being effected through the current technological revolution is evolving exponentially in comparison to other industrial revolutions (Schwab, 2016).

The presence of digital capabilities has now become a precursor to the organisations' future profitability and sustainability. The disruptions that arise in these constantly evolving digital technologies force organisations to make substantial investments in order to navigate the ever-changing business landscapes (Hirt & Willmott, 2014). To date, the main beneficiaries of this technological revolution have been consumers. Tasks that required manual interventions have become relatively more efficient and can be done remotely through the use of digital platforms. However, studies indicate that this industrial revolution could yield greater economic inequality as it has the potential to disrupt labour markets (Schwab, 2016). A large number of manual tasks in certain occupations are either being replaced or augmented by computerization, this puts a fair amount of risk on the level of employment in these occupations (Frey & Osborne, 2017). A 2013 study by Frey and Osborne concluded that, 47% of United States'(US) employment was at an elevated risk of job displacement attributable to automation. The study further stated that, occupations such as transport, logistics, administrative support, manufacturing as well as the services industry were at the highest risk of computerization.

Globalization has transformed the manner in which business is conducted on a global scale (World Economic Forum, 2017). Consolidation has led to a rise in competition as entities are able to leverage efficiencies across regions (Berger & Mester, 2003). The banking sector which at one point was among the biggest job creators is no exception as banks increasingly realize the need to transform business models for future relevance (Shukla & Rebello, 2017). The threat of non-traditional competitors such as Financial Technology Firm's (Fintech's) increasing their participation in practices traditionally reserved for the banking industry has adversely impacted the banking industry's profitability (John, 2017). Conventionally, banks make their revenues from fees and income derived from retail banking operations such as money transfers and realised gains from foreign exchange trading. Fintech's are able to provide this to the banking industry's consumer base at cheaper rates and banks with their lack of agility compounded by their traditional bricks and mortar model fail to compete with them (John, 2017). This has led to significant investments in the banking sector's digital technologies and ultimately it has also contributed to job replacements as cost reduction drives in the banking industry are responsible for task automation.

There is a view that job displacements as a result of technological advances will drive further economic inequality (Rockstroh & Rotman, 2013). Data shows that while in European nations the national income's labour shares is evidently declining, the United States' statistics are a little more modest as they are at six percent (Kristal, 2013). History has shown that every successive industrial revolution has eventually resulted in bigger scale productions but in a smaller workforce as labour has moved to more service oriented office jobs (Autor, 2015). However, the concern in this current industrial revolution is that technological change is preventing the economy from creating additional jobs as even jobs that are deemed as complex are being replaced by cognitive digital technologies.

Routine, low complex as well as repetitive tasks are being fully automated and it is becoming increasingly prevalent that cognitive tasks can also be automated (The Economist, 2016). Research undertaken by the McKinsey Group yielded interesting results as it was determined that, occupations in their entirety, cannot be fully automated in the short to medium term future (Chui, Manyika, & Miremadi Mehdi, 2015). However, activities in certain occupations have the potential to be fully automated which may require an entire business process to be re-designed and certain job descriptions would have to be redefined (Chui, Manyika & Miremadi Mehdi, 2015). Autor (2015) supplements this view by stating that automation replaces as well as complements labour. The author further argues that automation is able to increase productivity in ways that may necessitates additional labour. To counter this ongoing economic debate that over half of the jobs will be automated in the next two decades, Arntz, Gregory and Zierahn (2017) argue that this assertion completely ignores the task variation that human beings are able to achieve more as opposed to automated technology. Autor (2015) gives an example of Automated Teller Machines (ATM's) which were supposed to completely eliminate bank teller jobs but they could not handle all the jobs as bank tellers now had to switch job roles to do more advisory duties instead of the more elementary currency handling roles they occupied previously.

The disruptive nature of technological change can be immense. However, the pace of this disruption is specific to locations as certain legal and societal factors can influence the deployment of technology in a particular location (Arntz, Gregory & Zierahn, 2016; Kim, Kim & Lee, 2017).

1.2 Problem Statement

The prevalence of A.I as a phenomenon is quite apparent, however, the pace at which the digital technologies that complement it are adopted, varies across countries (World Bank, 2016). The 2016 World Bank study entitled, 'Digital Divides' summarised the main factors that may affect the adoption of digital technologies. These factors include mass digital access, skills inadequacy, labour re-shoring and regulation (World Bank, 2016). The developed world has been experiencing widespread labour polarization with middle-skilled routine occupations being at the most risk (Cortes, Jaimovich & Siu, 2017). However, in developing nations, there is evidence that there may be less middle level routine occupations as the employment statistics are skewed towards the informal sector (Maloney & Molina, 2016).

The banking industry has been a leader in the early adoption of digital technologies, however, the majority of technology based innovations have been based on non-traditional banking institutions (World Bank, 2016). The adoption rate of digital technologies can be determined by the knowledge of these technologies, access to these technologies, a complementary skill set to these technologies and finally the sector's competitive landscape (World Bank, 2016). The research's purpose is to expand on these particular factors that slow down the displacement effect of digital technologies in a frontier markets context. The banking industry is a highly regulated industry which leads to a convergence of business practices amongst industry peers. Zambia, in particular, is governed by the Basel III Capital Regulatory Framework and underwent a recent capital requirement ratio hike in April 2017 (Business Monitor International, 2018).

The researcher observed that research in this particular field has not focused on banking in a frontier markets context. In developing markets, the banking industry has undergone some transformation. Before the 2008 financial crisis, the rise of financial globalization had an inflationary effect on bank sizes as international banks expanded all over the globe (World Bank, 2018). Post-2008 has seen a reversal of this trend as international banks have exited these developing markets and interestingly there is an expansion of developing banks into neighbouring regions and this is known as regionalization (World Bank, 2018). There is a school of thought that this recent phenomenon may limit the absorption of best banking practice technology due to the capital constraints.

The banking industry is undergoing a period of significant technological change. This has been necessitated by disruptions caused by rapid technological advances, an increasingly demanding customer base and regular regulatory amendments and contradictions (Liedekerke & Dubbink, 2009). The purpose of this research is to understand the factors that influence the readiness of banking industry employee to adopt digital technologies, in particular, artificial intelligence (AI). The emergence of digital technologies has brought on forced changes onto the workforce in the banking sector. There is a general assumption that the workforce in frontier markets is apprehensive about change, under qualified and additionally under skilled. A large component of this research will be to determine the ability of the workforce in the banking sector in frontier markets to adapt to technological change. The scope of the research will be frontier markets and a deductive study will be done on the banking industry in Zambia. The proposed outcome of this research will be a regression model that can be replicated in similar industries in frontier and emerging markets, complete with any additional factors derived from the study. Currently, all prior research has been done on a national level, the researcher's contribution to research will be to understand the dynamics of these factors in a frontier markets context.

1.3 Academic Significance of Study

AI is a novel topic that is yet to be confined to a strict definition. It has been referred to as the act of computerised systems imitating and replicating tasks that are ordinarily performed by human beings (King, Hammond & Harrington,2017). The development of artificial intelligence stemmed from the need to complete tasks that are intuitively challenging for human beings but are considered practically routine by computers (Lee, Taylor & Kalpathy-Cramer, 2017). The artificial intelligence field is still not fully comprehended as it is coupled with the emergence of the fourth industrial revolution and the developments in and around the field are fast evolving. The term AI conjures up visions in many intelligent computer systems that are slowly taking over mankind thereby rendering them irrelevant. The term artificial intelligence was first coined in the early 1950's when the first usable computers emerged as precursors to unravelling the true wonders of artificially created intelligence (Russell, Norvig, Canny, Malik & Edwards, 1995).

AI is a diverse field with multiple definitions from various schools of thought. One clear interpretation of artificial intelligence is the creation and development of computerised systems that mimic human beings in terms of thought processes, certain actions and increasing rationality. The sphere of influence for the field of artificial intelligence involves an IBM chess program beating the then chess master Gary Kasparov in 1996. The AI field of research has unearthed various sub fields of the phenomenon. One particularly interesting subfield is the area of machine learning, which has an ability to simulate human learning through the use of algorithms that can process enormous amounts of data in record time (King et al., 2017). Through the use of AI, computer systems have the ability to perform complex tasks in the shortest possible timeframes. An increasing limitation for the advancement of artificial intelligence is the ability to mimic intuitive human actions (Lee et al., 2017). However, since the innate ability for technologies associated with AI is self-advancing, these challenges are rapidly being superseded.

Huang and Rust (2018) advance a theory of artificial intelligence in relation to its perceived job substitutionary effect. The theory is centred around service tasks and includes mechanical, analytical, intuitive and empathetic levels (Huang & Rust, 2018). Autor (2015), however, focuses on the job complementary effect of advancing technology. Huang and Rust (2018) hypothesise that as AI advances, computers will eventually replace human labour in not solely mechanical and analytical tasks but in intuitive and empathetic tasks as well. The disruptive nature of emerging technologies has significantly reduced innovation time lags and every firm that is willing to make advances needs to implement a technology driven strategy. The modern era customer demands personalization over standardization and relational service over transactional service (Huang & Rust, 2017). To remain competitively relevant, firms need to invest in technological opportunities that augment their service offerings to their client base.

The infusion of technology into interactions with customers is generally intended to augment the service offering in their customer's experience of the firm (Davenport & Kirby, 2015). The modern day customer is more empowered and more demanding than ever before, thereby prompting firms to invest significantly in not only service complementary technologies but in data analytical technologies as well in order to better anticipate evolving customer needs (Edelman & Singer, 2015). Contemporary research has alluded to the infusion of technology, creating interpersonal barriers to customer interactions with frontline staff, thereby, adversely affecting the customer experience (Giebelhausen, Robinson, Sirianni & Brady, 2014). However, very little research has gone into revealing the effects of intelligent technology that is mediated through learning in improving service efficiency and effectiveness (Marinova, de Ruyter, Huang, Meuter & Challagalla, 2017). Additionally, gaps remain in the research to uncover the effects of technologically enabled self-service platforms on customer affection (Meuter, Ostrom, Roundtree & Bitner, 2000). The researcher identified additional gaps in determining what drives the adoption of intelligent technologies and how ready are employees to adapt to it. The study aims to add to existing theory by investigating this particular phenomenon in a developing markets context.

1.4 Business Need for Study

Contemporary market research points to evidence of a large number of companies investing heavily in AI (Violino, 2017). Globally, data points to a third of companies that are placing long-term strategic importance on the impact of AI infused technologies and 32% of those firms are defined as being in the provision of financial services (Violino, 2017). The onset of the fourth industrial revolution has prompted a multitude of disruptions. The financial sector has not been spared as the digital revolution spurned on by the rapid global technological developments has challenged the banking sector's static brick and mortar business model(Temelkov, 2018). The modern technological era has encouraged the rapid and urgent demand by clients for cheaper and time efficient innovations. The banking industry which faces massive disruptions by the emerging Financial Technology firms (Fintech's) requires an adjustment of strategic intent in order to prevent itself from becoming obsolete in light of an increasingly demanding client base (Boeders & Khanna, 2015).

Most banks place significant strategic importance on being client centric. The Stanbic Bank Zambia's 2017 Annual Report places client centricity as one of its five year strategic pillars (Stanbic Bank Zambia, 2017). First National Bank Zambia (FNB Zambia) refer to superior client service as a core strategic thrust (FNB Zambia, 2018). Barclays Zambia have the following quote on their website, "*We believe in creating opportunities for our customers to make their possibilities real and supporting them every step of the way. Our group is a future-focused organisation, driven by progress and our desire to thrive in the digital age*". (Barclays Zambia, 2018). The emphasis on client satisfaction is clearly evident in these strategic statements. There is a significant shift from the common silo business model that most traditional banks employ as more banks are becoming more inclusive organisations that leverage off cross selling opportunities in order to become more relevant to their client base (Temkin, 2016). Technological pressure from Fintech's has evolved client centricity from a buzz word in banking circles to a strategic focus. The digital technologies employed by Fintech's have introduced mobility, ease of use, speed and lower costs to the average consumer (Saksonova & Kuzmina-Merlino, 2017). Traditional banks with their significant investments into brick and mortar may not possess the agility to effectively counter these disruptions.

Frontier markets is a term that was coined in 1992 by Farida Khambata to define nations which are relatively more developed than the least developing markets, but are still generally too small to be considered emerging markets. Fintech's are not yet a significant threat to the banking industry. The Fintech industry is still blossoming and has not developed significantly to become disruptive to the banking industry (Zalan & Toufaily, 2017). Presently, research points to selected customer and product segments that are being disrupted in developing markets. For instance, Mobile Network Operators and other emerging Fintech's such as Mpesa in East Africa have revolutionised the money transfer market. Once a staple product line of the traditional banking sector, the public can now access money transfer services from these Fintech's through the use of mobile cellular devices. However, frontier markets are not immune to the rapid developments in intelligent digital technologies. The pervasive spread of AI development globally will not fly over developing nations (Novitske, 2018). Business is already on the back foot as there are shorter innovation cycles being demanded by customers (Edelman & Singer, 2015). There is a risk of business remaining permanently reactive if they do not embrace digital technologies whole heartedly. There is a general cognisance of the need to digitalise, the greater question is if organisational workforces are ready to adapt to this technological change. If their workforces cannot adapt, the organisations will be left behind competitively.

Market research has cited leadership, regulation, budgetary limitations, customer expectations and inadequate skills as a few of the barriers of widespread AI adoption (Curran, 2017; Violino, 2017). The researcher will aim to investigate this gap through the lens of a developing nation's context.

1.5 Scope of the Research

The research is focused on uncovering the factors that predominantly drive the adoption of AI and employee readiness to adapt to AI, in developing nations more specifically in frontier markets. The research will target the Zambian banking industry in an attempt to formulate a model for AI adoption that can be replicated in similar industries. The study will utilise data collected from one of the major banks in the Zambian capital city as a representative sample of the Zambian banking sector.

1.6 Outline of Report

The next chapter will commence with a comprehensive literature review in order to identify the factors that influence the adoption of artificial intelligence. This literature review will gauge how prevalent these factors are. The literature review will in addition display a high level critical review of the theory surrounding digital technologies, in the context of artificial intelligence, which is an emerging topic. Finally, the literature review will highlight the possible business practice differences between banks that operate as regional subsidiaries and locally owned banks. The literature review will be concluded by an argument for the possible factors that influence artificial intelligence adoption in frontier markets based on the literature reviewed. The argument will be tested by research questions. The subsequent section will be comprised of a comprehensive description of the methodology that was employed to test the claims posed by the research objectives. The results collected from the data will then be presented and discussed in the two subsequent chapters. The document will then be concluded by a final chapter which will be expanding on the possible implications for business based on the limitations that were discovered during the fulfilment of the research study.

CHAPTER 2:
LITERATURE REVIEW

2.1 Introduction

The purpose of this study is to identify and understand the factors that influence the adoption of artificial intelligence in frontier markets, and employee readiness to adapt to AI. The following critical review of existing literature will unearth any theoretical base that was used to frame the research objectives. Below is a brief outline of how the literature review was conducted.

The literature review will commence with an overview of Zambian dynamics in regards the financial and banking sector. This section will mainly highlight any important statistics that are relevant to the study and introduce at a high level the Zambian banking environment. Thereafter, an analysis of existing academic literature, focusing on the definition of digital technologies such as automation as well as computerization and ultimately on artificial intelligence will follow. This section will aim to provide some theoretical background on why this is currently a topical issue. This section will be concluded with a high level overview of prior literature that analysed the effect of this phenomenon on the current world of work and any overarching justifications for business implementation.

The subsequent section will aim to uncover the factors that influence the adoption of certain digital technologies as outlined in the 2016 World Bank Development Report and it will use a theoretical lens. It will further aim to uncover any additional factors that delay AI adoption with the aid of theory. This section will assess how prevalent these factors are in existing literature and using literature it will aim to predict their effect on the workforce in developing markets.

The final section of the literature review will aim to establish any cardinal differences in business practices between foreign and locally owned banking institutions. Furthermore, it will briefly explore the frontier markets concepts. The literature review will lead to the framing of the research questions which will follow this particular section.

2.2 Overview of Zambian Dynamics

Zambia is a landlocked country located in Central Southern Africa, bordered by eight other African countries. The most recent estimated population figures for Zambia are 17.6 million people(Zambia Population 2018, n.d.). Zambia obtained independecet from British colonial rule on the 24th of October, 1964. The Government system in Zambia has undergone three separate transitions since Independence, namely, a multi-party political system from 1964 to 1972, a one party state from 1972 to 1991, and reverted back to a multi-party system since 1991 (Zambia Central Statistical Office, 2018). The President of Zambia is elected through a popular vote of 50% plus one every five years (EuroMonitor International, 2018). The current President is Edgar Chagwa Lungu, elected in August 2016. Zambia is divided into ten administrative provinces and 105 official districts (Zambia Central Statistical Office, 2018). Lusaka is the administrative capital city and is additionally the financial hub of the country.

The main industries in Zambia are agriculture, mining and manufacturing. The agriculture sector accounts for the employment of 50.40% of the workforce (EuroMonitor International, 2018). The main exports of the agricultural sector are cotton, coffee, tobacco and maize. The manufacturing industry is comprised mainly of producers or processed food and engineering accompaniments like copper cables, it employs 5.10% of the workforce and contributes 11.00% of the Gross Domestic Product (GDP). Zambia is the second largest African producer of copper and seventh largest globally (EuroMonitor International, 2018). The mining industry is responsible for approximately three quarters of the country's export earnings, but has undergone frequent friction with the Zambian Government concerning recurrent changes to the governing tax policy. Several of the mining companies in Zambia have been privatised. Zambia's substantial reliance on the export of copper for foreign exchange leaves the country's quite vulnerable to economic shocks caused by commodity price fluctuations (BMI Research, 2017).

There are currently 19 registered commercial banks in Zambia (Bank Of Zambia, 2017). The Zambian banking sector is viewed as relatively stable but is dominated by the existence of subsidiaries of foreign domiciled banks. Recent statistics refer to approximately 70.00% of the total assets, loans and deposits, primary products of the banking sector are reportedly accounted for by foreign subsidiaries (BMI Research, 2017). Of the 19 registered commercial banks, eight of them are foreign owned, nine are local banks, while two are joint ventures with the Zambian Government. (BMI Research, 2017). The industry is poised to exhibit growth in the coming years with progressive monetary policy implementations by the Central Bank. There is perception that the sector has a limited product offering in comparison to more developed sectors in the region (BMI Research, 2018). Additionally, there is a general assumption that majority of the workforce in Zambia is lowly skilled, which is evidenced by the sluggish rates of innovation in the economy. However, the emergence of Fintech's is ensuring that the Zambian banking sectors develops its technological capabilities in order to compete favourably.

2.3 Emerging Technologies

The rapid pace of technological change that the world is experiencing is unprecedented. Emerging technologies that have the equal ability to either disrupt or enable the world of business are being brought forward as regularly as they are being discovered. Innovation cycle time lags have reduced significantly. The pertinent question business is left to ponder is, how to successfully integrate these pervasive innovations into their dated business models. There has been an increasing level of interest and debate on the classification of emerging digital technologies. As technological change remains a constant in the people's everyday lives, the debate rages on. Contemporary research has attributed five aspects to the classification of emerging technologies namely *(i) Radical novelty (ii) Relatively rapid growth (iii) Coherence (iv) Prominent impact (v) Uncertainty and ambiguity* (Rotolo, Hicks & Martin, 2015, p. 1828).

The challenges of adopting emerging technologies in order to remain competitive in business, lie in the rapid and disruptive nature of these technologies (Bildosola, Río-Bélver, Garechana & Cilleruelo, 2017). Their novelty and impacts are far-reaching and in that sense they are difficult to measure as their evolution is almost as rapid as their development (Rotolo et al., 2015). Technological change has been defined in literature as, "*the technological progress of incremental, continuous change and of radical, discontinuous change at an industrial level*" (Hung & Tu, 2014, p.1227). Hung and Tu (2014) use the chaos theory adapted from Edward Lorenz's 1963 study on the "butterfly effect" to demonstrate how impactful technological change can be on an industrial level despite the sometimes perceived small size of the change itself. In order to retain a competitive edge, it has now become imperative that firms not only invest substantially in the infusion of digital technologies into their business models but also equally in the monitoring of these technologies. The monitoring of emerging technologies can augment the efficiency of research and development endeavours at a firm level (Joung & Kim, 2017).

However, as critical and as beneficial as emerging technologies may be, there is an overwhelming lack of emphasis on the ethical, societal, commercial and regulatory implications in contemporary research (Groen & Walsh, 2013). There has been some debate that is focused on the substitutionary or complementary effects of emerging technologies, but it has no clear cut conclusions. The business need to significantly invest and monitor emerging technologies is apparent, however, the quantification of the benefits derived from these investments is not as explicit. Frontier markets and Africa, in particular, are in theory lagging behind in the adoption cycles of the majority of these technologies, but their rapid disruptive nature indicates that this may not be the situation for long. A large number of global firms have deliberate digital strategies that are aimed at market developments in developing nations

(Thukral et al., 2008). However, certain adoption barriers exist in these developing markets and this may be unique to different regions. Further comprehensive research is required to reveal these factors.

2.3.1 The Definition of Artificial Intelligence

Artificial intelligence is a robust form of emerging technologies. Although the term was coined in the latter part of the last century, the field has recently come into prominence with the emergence of the fourth industrial revolution. As with most modern trends, no clear cut theoretical definition exists of the term. King, Hammond and Harrington (2017, p.53) define AI as, "*the study of computer systems performing tasks that would normally require human intelligence*". The challenge of assigning one strict definition to the field lies in the fact that the field consists of several subfields. One popular sub field is machine learning which has been defined as, "giving computers the ability to learn without being explicitly programmed," a definition that was attributed to Arthur Samuel, a thought leader in the sub field of machine learning (Lee et al., 2017). The proponents of machine learning point out time advantages and lack of secondary programming among their support for machine learning. However, another school of thought agrees that while AI can cause computer systems to learn, can they reason? Bottou (2014, p. 136) defines reasoning as, "*algebraically manipulating previously acquired knowledge in order to answer a new question*". The author further argues that human beings are not limited by the need to endure a process of logical and probabilistic inference in order to derive what simple reasoning (Bottou, 2014). It can be inferred that there is a limit to the number of cognitive tasks that can be addressed by linear programming without the addition of multiple layers of computational methods (Bottou, 2014).

2.3.2 Artificial Intelligence in the Frontline

It is widely acknowledged by business leaders that there is a need to embrace and significantly invest in technology in order to remain competitively relevant. Technology which includes the use of AI will deliver less costly and more personalised services to customers, due to it being more thorough in data analytics. The comprehensive automation of back office processes is a popular line of reasoning amongst business executives in order to deliver superior customer service (Crabb, 2017). More empowered customers are demanding that less time and money be spent on services which they demand to be personalised (Edelman & Singer, 2015). It has become almost imperative for business to formulate strategy embedded with deliberate digital strategic objectives. It is commonplace now for every service strategy to be underpinned with digital goals and purposes (Huang & Rust, 2017; Turel & Bart, 2014). The infusion of technology into automating the back end processes, in addition to the injection of more cognitive technologies into the frontline theoretically makes service to customers more efficient and effective (Marinova et al., 2017). The notion that cognitive technologies must be interpolated into frontline operations in order to improve effectiveness does make sense. The learning algorithms and complex data analytics make every customer interaction an experience. The reason is that at the next interaction with the client, the firm is better informed on the client's tastes and preferences and can offer a more personalized service.

Cognitive technologies such as artificial intelligence can augment service efficiency and effectiveness by not only automating processes but additionally by facilitating that knowledgeable workers be given complex tasks due to their analytical superiority (Davenport & Kirby, 2015). It has been previously discussed how cognitive technologies enhance interpersonal relations with customers due to their improvement of service delivery. As customers demand more personalization, it would be safe to assume that they would want their voices to be heard. The infusion of technology into customer – firm interactions has the ability to reduce interpersonal rapport between the customers and frontline firm representatives (Giebelhausen et al., 2014). In addition, the emergence of self-service technologies further reduces the rapport building that most service orientated firms thrive on in their client centricity models (Meuter et al., 2000). The double edged sword that is the impact of artificial intelligence in business is twofold. Research has shown how it is necessary for competitive growth and service augmentation. However, the implementation of these technologies does have an economic impact in terms of its eventual and arguable labour substitutionary effect. The question is, how worthwhile is it for business to implement in developing nations that are still grappling with rising unemployment dynamics? So far, certain regulation and other societal and cultural factors in these nations have prevented a widespread adoption of artificial intelligence. However, increasing demands from a customer base that demands cheaper, more relevant services are shifting towards ultimate extensive adoption. It would be imperative for business to fully understand the adoption barriers in the context that they operate in.

2.4 The Impact of Digital Technologies on the Workforce

The debate on task automation has progressed beyond the replacement of low complexity, repetitive and routine tasks. The current debate is on cognitive technologies. Cognitive technologies are evolving technologies that are equipped with machine learning functionalities and they can deal with tasks that are characterised by higher levels of complexity (Noor, 2015). Statistics from the United States show that industrial robots can take on larger tasks and they can replace up to 1,000 human workers (Acemoglu & Restrepo, 2017). Automation of tasks occurred in the banking industry when ATMs replaced human tellers (Autor, 2015). Although job losses were prevented due to job redesigns and tellers taking more advisory roles, cognitive technologies are able to even replace complex roles such as loan underwriters in the banking industry through the use of algorithms (Shukla & Rebello, 2017). Developments in the field of cognitive technologies state that they are designed to operate like the human brain, but at a more advanced pace (Noor, 2015).

John Keynes predicted eventual, widespread, technologically induced unemployment due to the emergence of computerization in the workplace (Frey & Osborne, 2017). Increased unemployment leads to widened income inequality and US data already displays a reduced labour contribution to the national income due to the loss of employment that is directly attributed to automation (Kristal, 2013). In increasing instances, it has been determined that automation can substitute human labour. Technological adjustments to activities performed in work occupations have led to some level of unemployment, however, it is also forcing a restructuring of job design (Autor, 2015).

The past thirty five years in the United States have seen an increase in the unemployment of the middle skilled. This has been linked to a gradual departure from workers undertaking routine occupations due to the prevalence of digital technologies such as automation (Cortes et al., 2017). Key to this economic debate is a view that there has been an over estimation of the gravity of job losses that are attributed to technological change (Arntz, Gregory, & Zierahn, 2017). This view is supported by the assertion that permanent job loss is occurring because there is an increased prevalence of labour market polarization, a situation where the job market hollows out in the middle (Autor & Dorn, 2013; Graetz & Michaels, 2017).

Artificial intelligence is a more emerging topical form of digital technology. One definition states that it is the development of technology that replaces tasks that were previously done by human beings with computer systems or automation (Nilsson, 1999). Nilson (1980), a leading author in the field states that there are a number of different AI applications, including but not limited to language processing, robotics, automatic programming and intelligent database systems (Nilsson, 1980). However, for the scope of this research, focus will be solely on the definition provided above. The AI applications are constantly evolving and even include cognitive technologies which are able to perform tasks that human beings have never been able to achieve such as machine learning and computer vision (Schatsky et al., 2015).

Frey and Osborne (2013) predicted that 47% of the occupations that they analysed would be extinct in the next 10 to 15 years. However, their study focused on occupations and seemed to ignore the range of other tasks which would be difficult to automate (Arntz et al., 2016). This leads to a narrative of an over estimation of the substitutionary effect that the digital technologies may have on jobs. An alternative school of thought goes further to suggest that some employment may actually be created from the prevalence of digital technologies (Kim et al., 2017).

The quantum of job losses that are directly attributable to technology may be overestimated and this may be more prevalent in the lower skilled occupations. However, there is a need for skill augmentation in the workforce in order to prevent this from becoming a challenge as this may lead to significant job re-design (Arntz et al., 2016; Autor, 2015). Developing nations, that may have been beneficiaries of increased economies of scale as a result of globalization will be affected as cost benefits of re-shoring labour to cheaper geographies will decline as a result of evolving technological change (Siddhartha & Luc, 2017).

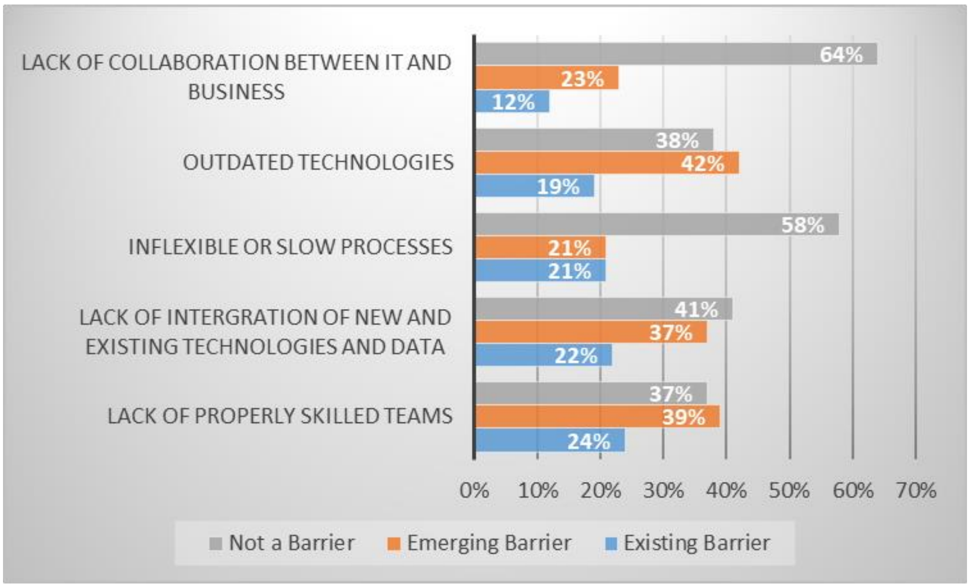
In recent years, the strategies that are centred around information technology have taken precedence in organisations and at times they have been accorded more prominence than business strategy (Bharadwaj, El Sawy, Pavlou & Venkatraman, 2013). Consumer behavioural trends have shown an affinity for consumers to embrace any product or service that limits the amount of manual intervention to complete and provide them with a convenient way to complete the transaction (World Bank, 2017). For an organisation to compete favourably in this current technological revolution, it will require noticeable investment in digital technologies.

Further research is required to determine the readiness of employees to embrace and adapt to digital technologies in developing nations.

2.5 Factors that Influence the Adoption of Artificial Intelligence

The World Bank states that the adoption of digital technologies can be low in non Information and Communications Technology (ICT) firms due to the variances in income levels, sector characteristics, management capabilities, high importation costs of digital goods and services as well as market conditions and disruptions (World Bank, 2016). The main motivation to embrace and exploit digital technologies stems from the capitalist theories of profit maximisation and cost reduction, which can drive further economic inequality (Spencer, 2018). A further study conducted by PricewaterhouseCoopers in 2017 uncovered some additional factors that can be attributed to the slow pace of digital transformation in organisations. These factors are summarised in the following table.

Figure 2.1: Factors that delay digital transformation efforts



Adapted from (PricewaterhouseCoopers, 2017), pg. 19

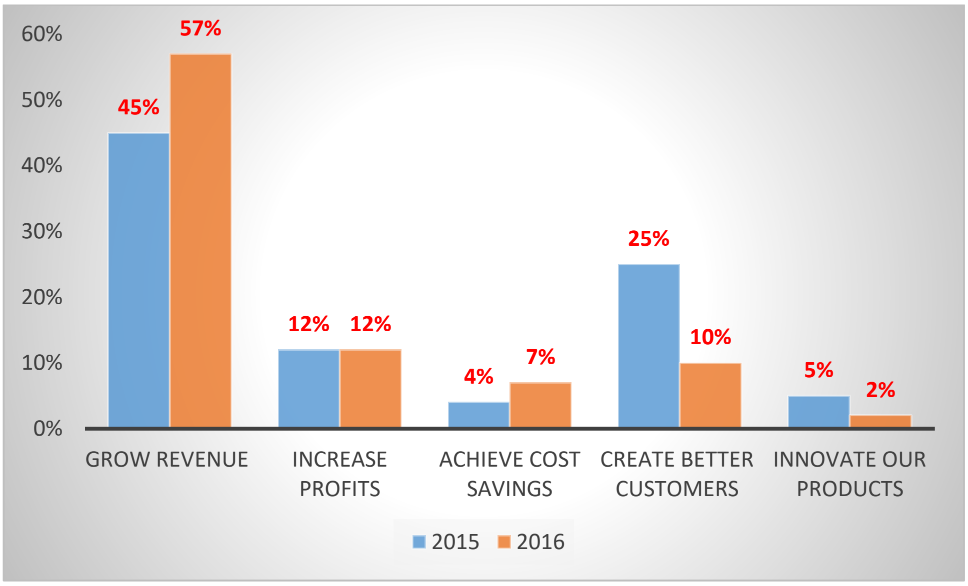
Past practice in firms highlighted that Information Technology (IT) strategy is driven by a more broadly encompassing business strategy (Bharadwaj et al., 2013). Recent improvements in digital technologies combined with the easing of costs to acquire technologies have given significantly more prominence to the firms' IT strategies. The evolution of technology has led to the emergence of cognitive technologies and human beings are now being subjected to competing for jobs with these intelligent machines (Pupo, 2014). Increasing efficiency, which has a direct effect on the bottom line growth is a cardinal motivator for firms. This is supported by sluggish employment growth over the last few years as task automation has replaced occupations that were previously held by human beings (Rockstroh & Rotman, 2013).

An alternate school of thought states that technological change should be embraced as a precursor to prosperity. However, this can only be possible with policy interventions regarding skill augmentation and protective regulation (Siddhartha & Luc, 2017). As digital technologies continue to improve, it is cardinal for developing nations to institute active labour market policies in order to curb unemployment shocks (Mckenzie, 2017).

2.5.1 Leadership Clarity

The need for increased technological investment is evident in today's fast paced world. However, it does seem that there is a time lag between the recognition of this need and the actual implementation of complementary technologies. A school of thought points to managerial capabilities as significant factors in the implementation of digital technology. Firms have multiple executives with overlapping responsibilities and thus digital strategy does not have direct ownership (Curran, 2017). The importance of a digital business strategy is more relevant than ever in the current era (Bennis, 2013). The findings of the global 2017 PricewaterhouseCoopers survey conducted with 2,216 firms revealed that revenue growth is still a primary focus area for a multitude of firms (PricewaterhouseCoopers, 2017). Below is an adaptation of the survey results which posed the question of what expected areas would yield the most return from digital technology investment.

Figure 2.2: Value Expected from Digital Technology Investment



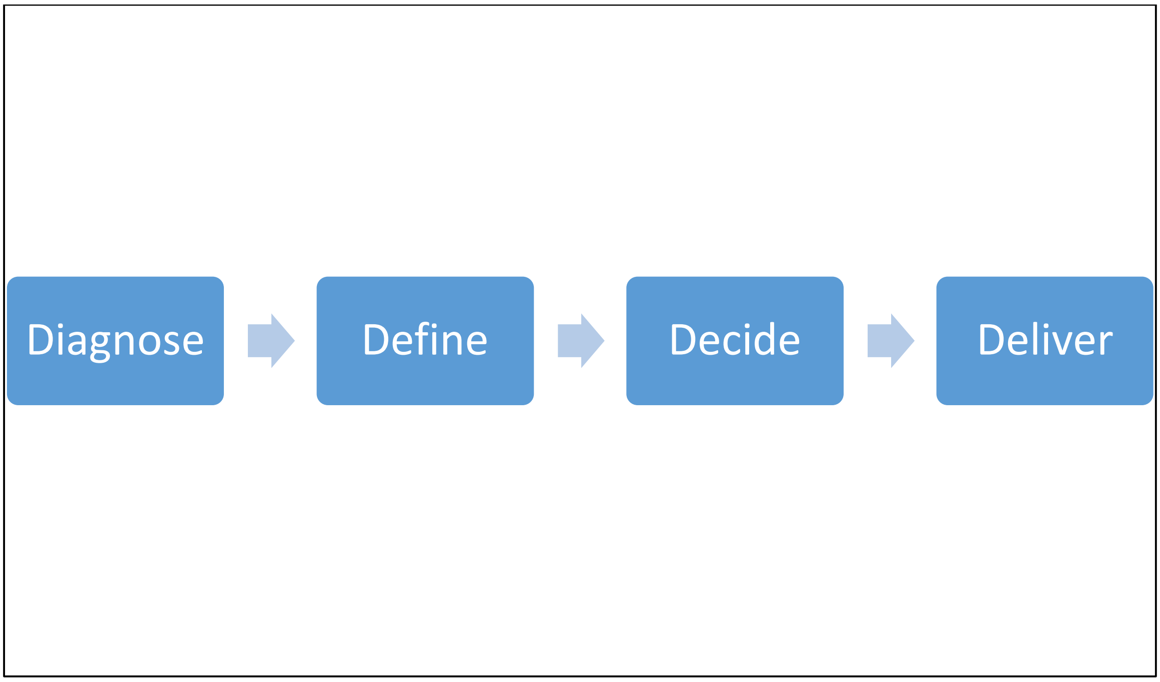
Adapted from (PricewaterhouseCoopers, 2017), pg. 16

An important aspect of digital technologies lies in the dissemination of information. Technology enables firms to be a lot more aware of the environments in which they operate in as information can be readily available to them through the use of technology. This will enable a firm to comprehend their client base a lot more thoroughly as the feedback loop is a lot more efficient and in turn should translate to more efficient decision making (Bennis, 2013).

Business executives recognise the importance of being adaptive to digital technologies in order to remain competitively relevant and evidence of this is visible in a multitude of firm strategies placing an emphasis on digitalising many of their processes (Berman & Dalzell-Payne, 2018). The sheer pace of change has necessitated that the mandate of digital strategy does not remain marooned in the information technology department, but for the majority of firms, the digital strategy is now the mandate of the Chief Executive (PricewaterhouseCoopers, 2017). Modifications in the C suite have propelled chief information officers to become more strategic partners to the business, rather than business enablers. The term C Suite is usually used to describe high ranking corporate officers and directors in organisations, it is colloquially referred as the C suite due to the letter C, at the beginning of most high level corporate designations, for instance Chief Executive Officer.

The true value that emerging technologies can contribute to a firm is maximised when a firm's digital strategy is embedded in the value creation process from inception (Turel & Bart, 2014). This does not seem to be widely pursued in today's business environment, as the majority of business models begin with a business strategy, after which a decision is then made of the technology that is required to accompany that strategy (Berman & Dalzell-Payne, 2018). Below is an adaptation of incumbent business models that are used when developing strategy and the technology that is utilised to accompany the strategy.

Figure 2.3: Classic Strategy Development process



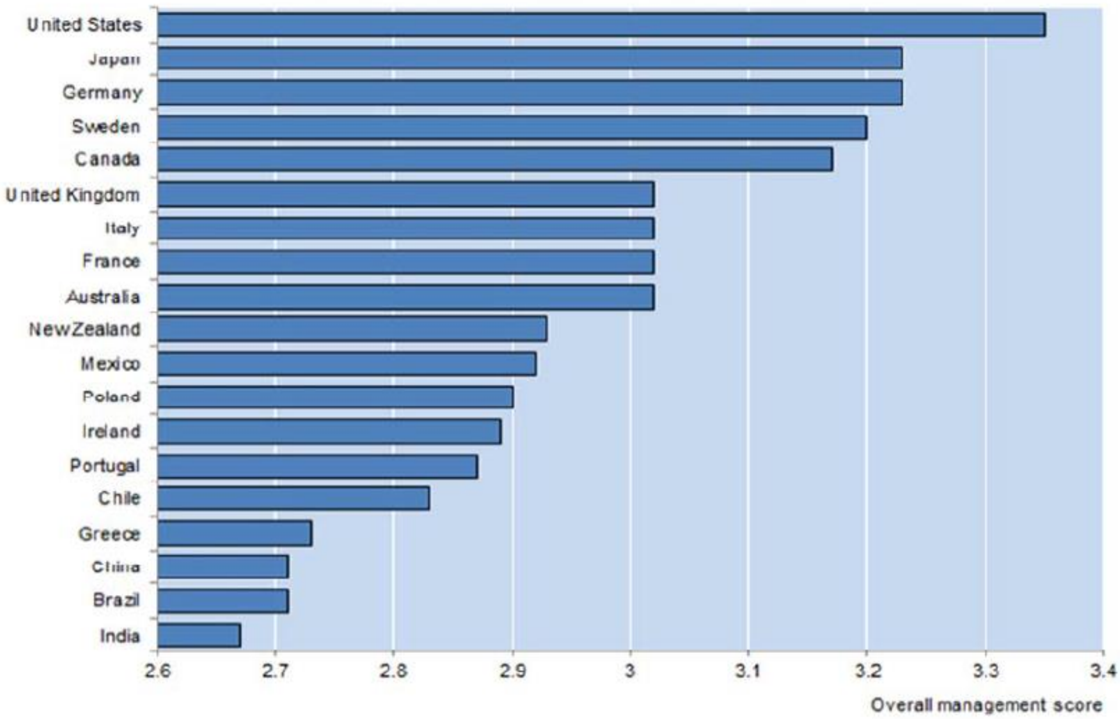
Adapted from (Berman & Dalzell-Payne, 2018) p. 11

Classic strategy development would only rope in technological and organizational capabilities in the latter stages of the process. However, more recently, there seems to be a realisation that technological capabilities should be developed during the initiation of the business strategy development and not subsequent to the fact (Berman & Dalzell-Payne, 2018). There is a clear need for alignment between business strategy development and the development of technological capabilities in firms, regardless of their size (Li, Liu, Belitski, Ghobadian, & O'Regan, 2016).

There currently exists evidence of strategy prioritisation concerning emerging digital technologies in firms, as more chief executives take ownership of technological advances. However, every firm has multiple business platforms and the emphasis on a continual need for innovation needs not rest with senior members of the firm solely as replication throughout the firm is required. Such an initiative needs to be driven by the firm's top executives (Alos-Simo, Verdu-Jover, & Gomez-Gras, 2017; Lu, 2015). It is commonplace for different departments in a firm to develop their own respective strategies, due to the silo nature of several organisations. It is, however, imperative that there is an alignment of organisational incentives and strategy developments across the organisation (Atkin, Chaudhry, Chaudry, Khandelwal, & Verhoogen, 2017; Reynolds & Yetton, 2015).

Recent research has shown that managerial capability is a significant factor in firm productivity. Statistics show that managerial quality scores are significantly higher in developed countries and considerably lower in emerging market economies (Andrews & Westmore, 2014). Below is an adaptation of managerial quality scores from a sample of Organisation for Economic Co-operation and Development (OECD) countries.

Figure 2.4: Managerial Quality Differences Across Countries



Adapted from (Andrews & Westmore, 2014) pg. 9

There are topical studies that have led with the argument that the pace of technological adoption and diffusion in firms is determined by the employees' levels of skills and the firm's agility when responding to technological change (Conti & Sulis, 2016). Due to the more mechanised nature of developed economies, it is prudent to make the assumption that the rate of adoption is higher in developed economies, rather than in developing economies, with the determining factor being the workforce's skill level.

Bennis (2013) emphasises the need for leaders in this new technological era to exhibit adaptive and agile characteristics in order to thrive. Further research conducted by Shao, Feng and Hu (2016) suggests that leadership styles need to adjust to the stages of technological diffusion in an organisation. The authors' central hypothesis stated that, "Transformational leadership is essential during the adoption phase, while transactional leadership is essential during the implementation phase" (Shao, Feng, & Hu, 2016, p.132). The pace of innovation that is required for firm longevity and relevance in a rapidly changing technological world may necessitate some form of cultural shift in organisations, this is the sort of terrain that transformative leaders can navigate successfully (Alos-Simo et al., 2017).

It is commonplace for leaders of most organisations to have shortened tenures at the helm of the organisation. Any form of investment in AI or in any other digital technology is long term. Most chief executives' mandates vary between three to five years. The individuals who replace incumbent executives may not place the same priority on a digitization drive. This research study will aim to gauge whether organisational leadership clarity can impact the adoption of artificial intelligence in the Zambian banking industry.

2.5.2 Workforce Skill Level

While there is a general realisation among executives in the business world that there are numerous benefits of machine learning applications and the necessity of digital technologies, there seems to be an ignorance of the requirements of an upgrade in the employees that are tasked with the operation of the said technologies in terms of their skills level (Ross, 2018). The emergence of technology initially occurred with an accompanying fear of rampant job loss, as automation and cognitive technologies replaced human labour (Frey & Osborne, 2017). However, time and further research has proven that the substitutionary effect of technology may have been overstated in earlier research and that technology ends up being complementary to human labour, although it requires some form of alterations in job design (Arntz et al., 2017; Autor, 2015). Cognitive technologies have the ability to improve the manner and pace in which a firm has access to information by means of its data processing abilities. However, there is a need for the personnel who are entrusted with the interpretation of the processed data to be fully conversant with the technologies and their processes (Ross, 2018). The emergence of more service oriented firms has also equally increased the skill premium for human labour (Buera & Kaboski, 2012).

Contemporary research has shown that although the emergence of technology has compelled the improvement of skills, it does, however, seem that this advancement of skills is at a slower pace than technological change (Berger & Frey, 2016). Further research has added to that narrative by placing emphasis on the executives' flaws in decision making as they sometimes incorrectly interpret data derived from Management Information Systems (MIS) due to a perceived deficiency in skill level (Lyytinen & Grover, 2017). It would be safe to assume that the rapid pace of technological advances can correlate to the firms' global productivity. The time lag can, however, be attributed to the development of complementary capabilities, which include human labour aspect skills (Brynjolfsson et al., 2017). This is but one facet of the "IT productivity paradox".

Decision making in recent times has relied on big data analytics rather than management intuition. Information driven decision making has a positive correlation to industrial productivity, however, research across a spectrum of industries indicates a time lag in implementing the use of data driven analytics. This is attributable mainly to complementary services requiring further development prior to any implementation of technology. One significant pre requisite to the success of data driven analytics is educated employees (Brynjolfsson & McElheran, 2016). Although existing research points to an increase in big data adoption, which implies increased emphasis on employee skill upgrading, the researcher believes that a gap still exists in adequate preparation for the managers who lead the employees that are entrusted with data science roles (Carillo, 2017). The majority of emphasis is placed on training the data scientists while limited emphasis is placed on adequately preparing the managers who supervise the data analysts. This research study will aim to understand if employee skill levels can impact the adoption of artificial intelligence in the Zambian banking industry.

2.5.3 Employee Attitude during Technological Change

The role of technology as an enabler to organisational performance has been documented quite thoroughly in contemporary research. Digital technologies have the capability of not only enhancing workflow in firms but they additionally service a firm's client base. Recent findings, however, point to the work force that use technology as more of an alteration to their work process and design, and less of an enhancer of service delivery (Yeo & Marquardt, 2015). Employee readiness for change has been defined in recent research as the, "*employee's feelings, beliefs and intentions about an organisation's strategic change that may provide variations in their routine working practices and procedures, as well as the organizational capability and capacity of its successful implementation*" (Adil, 2016, p.225). This technological era has the ability to bring about frequent and significant organisational change. The growing role of digital technologies in business is evidenced in the sustained use of self-serving technologies, which at their emergence employees may have been apprehensive about due to their perceived job displacement effect (Parasuraman, 2000). Prior research concentrated on the objective effects of change processes and less emphasis was placed on the individual experiences and outcomes of organisational change for separate employees (Rafferty & Jimmieson, 2017).

Rafferty and Jimmieson (2017) argue that the magnitude and frequency of organizational change were the main factors that would influence employees' resistance or acceptance of the change. In other words, the larger the magnitude of the change, the significant alterations in the employees' job design and this may have an effect on the employees' vision of their psychological contract. The authors also hypothesised that the larger the magnitude of change, the more apprehensive employees would be of the change. Additionally, the frequency of change in an organisation has direct correlation to the employees' resistance to change.

For any change initiative to be successful in an organisation, employee commitment is a pre requisite. Recent research has drawn links between the depth of relational psychological contracts and employee commitment to change. Relational psychological contracts have been defined in past literature as ones where both parties in a contract have a mutual obligation to honour each other's interests. Transactional contracts are short termed and usually relate to an exchange between the two parties (Guo, Gruen, & Tang, 2017). It would be safe to assume that employees with high relational contract values would exercise significantly more enthusiasm with regards to change initiatives in the organisation that employs them, than the employees with high transactional contract values (Jing, Xie, & Ning, 2014).

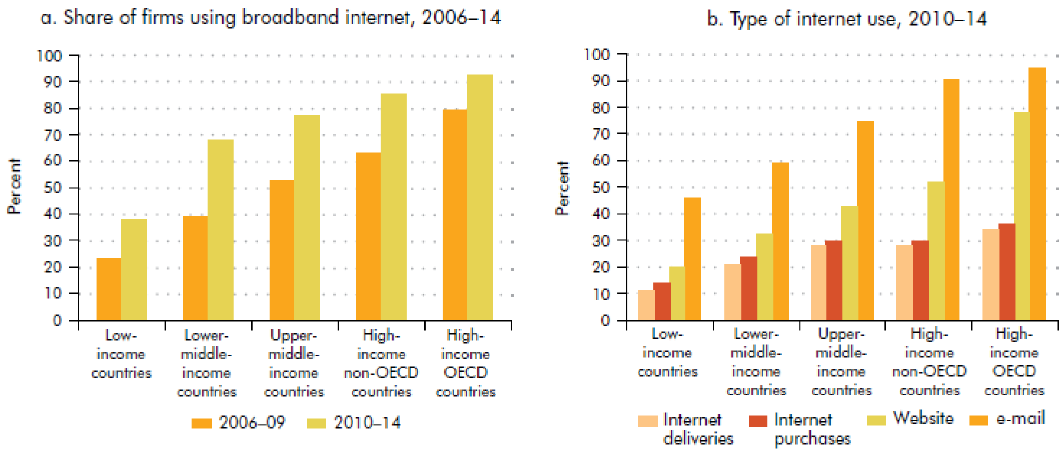
Organisational learning can ultimately lead to lower change cynicism in employees. Recent studies have discovered strong positive correlations between organisational learning and successful organisational change. Employees can exhibit a lack of change readiness and resistance to change initiatives due to a lack of sufficient knowledge on how to proceed subsequent to the change implementation (Imran, Rehman, Aslam, & Bilal, 2016). In addition to organisational learning, human resource divisions are critical when embarking on a change initiative. Oftentimes, the employee's perception of the change initiative is shaped by the practices that are being exhibited by their human resource division. Studies have discovered that it is imperative for human resources to institutionalize practices that are supportive of the change initiative that the organisation is undertaking in order for it to be successful (Maheshwari & Vohra, 2015).

Employee perception of any change initiative can prove to be significant during the change process. Today's business world with heightened customer awareness and rapid technological advances may require hasty change processes in organisations in order for them to remain relevant. The adoption of digital technologies is a relatively recent concept in developing nations and apprehension surrounding its usage is expected. This research study will seek to understand if employee attitude to change can impact the adoption of artificial intelligence in the Zambian banking sector.

2.5.4 Access to Internet

Many advanced digital technologies including those in economically developed countries have not widely diffused (World Bank, 2016). It would be safe to surmise that the usage of digital technologies is significantly higher in developed nations. The World Bank conducted multiple surveys in a longitudinal study between two time periods, 2006 to 2009 and 2010 to 2014. The results of that particular study are summarised in the chart below.

Figure 2.5: Global Usage of Digital Technologies



Adapted from (World Bank, 2016), pg. 52

The global usage of internet and additional digital technologies have clearly increased over the years. The benefits in terms of competitiveness and development that can be achieved from the widespread diffusion of digital technologies are apparent (Haenssgen, 2018). However, advances in digital technologies are not fully inclusive of the majority of the population in low-income nations. The progressive nature of these advances has the potential of excluding a large proportion of the population in developing nations, leaving them worse off (Haenssgen, 2018). An alternate argument points to the view that any investments made on digital technologies in developing or emerging nations do not translate into the gains enjoyed by developed nations (Niebel, 2018). However, this may be attributable to other factors such as the lack of sufficient skills and not so much to the extent of digital diffusion.

The financial industry is awash with ever improving technical solutions. The emergent threat of Fintech institutions is forcing more traditional financial institutions to consider significant investments to fend off these disruptions. However, globally, over two billion people have no access to financial services (McKinsey & Company, 2016). The majority of these individuals are located in developing nations and it has been discussed extensively how technology can foster economic growth. However, it is alarming that such a large number of people would be excluded from a formal financial system. Solutions proposed by institutions such as McKinsey & Company suggest options that are equivalent to the digitization of a large part of the financial system to make it more inclusive to everyone. However, that would entail making accessibility to services such as broadband internet more affordable in developing nations, in order to reduce the digital inequalities being experienced by many (Robinson et al., 2015).

It has been suggested that the rate of technology diffusion is a lot more favourable when it is inexpensive, convenient, has high potential benefits and is tailored to a local context (World Bank, 2016). It is interesting to note that most developing nations have highly diverse cultures. For instance, Zambia alone has 72 national dialects. It would then be safe to surmise that language and/or culture can be a significant barrier in the diffusion of digital technologies. An econometric analysis of Information and Communication Technology (ICT) diffusion conducted in Paraguay revealed that the heterogeneous nature in which technology is diffused in multi-cultural societies does more to deepen the digital divide than bridge it (Grazzi & Vergara, 2012). Consequently, Africa is, however, the global leader in mobile money transactions (Chironga, De Grandis, & Zouaoui, 2017). Mobile money transactions are a convenient and simple form of transferring funds. Inexpensive cell phones are the primary mode of communication. Additionally, in developing areas where there are significant distances between built-up urban zones, it becomes a very appropriate medium of financial exchanges. An addition to the argument of cultural barriers in technology is its role in the collection of data. Most customer facing businesses will perform data collection in one form or another in order to improve their customer experience. This act may, however, infringe on the traditional or cultural beliefs of the customer base, or may even be deemed as an invasion of privacy (Ekbia, 2016).

A population's access to technology is an important factor when a firm attempts to disseminate some form of technology across their customer base. This study will aim to put across the hypothesis that the adoption of artificial intelligence is slow in developing countries because firstly, the forms in which it may manifest itself are too complex for the majority of the target audience. Secondly, the cost of the necessary technology to access the products are still prohibitive in developing nations. Finally, language and culture are dominant barriers in scaling up any form of technology drive in developing nations.

2.5.5 Cost of New Technology as opposed to Human Capital

The existence of higher wages in developed nations strengthens the case of task automation in jobs and the greater prevalence of digital technologies (World Bank, 2016). However, due to the slower pace of industrial development in emerging market economies, workforce wages are substantially lower than their colleagues in developed countries (Ugur & Mitra, 2017). Technological changes will affect employment levels by re-defining the skills mix of potential employees (Castro Silva & Lima, 2017). Additionally, research has shown that advances in technology are skill biased in the sense that low complexity jobs can and are being replaced and technology which will lead to an increased demand for better skilled employees (Ugur, Awaworyi Churchill, & Solomon, 2018). This puts forward the argument that any investment into AI related technology would have an initial substantial capital outlay. This investment would far outweigh any staff related costs to compensate a firm's human capital for performing similar tasks. Therefore, organisations would be more inclined to maintain their human capital complement as an alternative to improving their service delivery through a significant technological investment.

The resource based view places great emphasis on the role played by an organisation's internal resources, which are inclusive of their finances to achieve and sustain a competitive advantage (Dyerson, Spinelli, & Harindranath, 2016). An organisation's capability to invest in any form of benefit inducing improvement is heavily dependent on their financial standing. The primary motivation for any organisation to infuse any form of technological developments into their processes is a quest to achieve benefits that outweigh the initial cost of implementation (Haug, Graungaard Pedersen, & Arlbjørn, 2011). There still exists some organisational anxiety regarding the risk reward of an investment in digital technologies.

Industry experts are well aware of how substantial an investment into a long-term technological outlay will be. In addition, there is also a realization, especially in emerging market economies, that the under development of IT infrastructure will require more investment (Violino, 2017). There is, however, a hesitant uncertainty regarding the time lag between capital outlay and tangible benefits and in addition, the complexities that come with AI (Atolagbe, 2017; Novitske, 2018). Artificial intelligence will not replace human capital in Africa's foreseeable future, but human labour will rather become a complementary force to technological advances (Sillah, 2015). This may translate to additional expenditure by firms who already are wary of worsening their cost to income ratio and due to the competitive landscape require a more immediate return on investment.

Contemporary research has alluded to the compensation theory initially put forward by Karl Max in 1867. One component of this theory focused on the lowering of wages that would come as a result of new technological investments. It was argued that a price adjustment in the labour market would lead to renewed demand for labour and this would compensate for the initial job losses, assuming that there is perfect substitutability between labour and capital (Vivarelli, 2014). A flaw in this theory is the neoclassical assumption of labour being a perfect substitute for capital and vice versa. Additionally, the theory also ignores the varying skill levels across a workforce. Existing narratives additionally emphasize the complementary relationship between labour and technology as job designs can change with the emergence of technology (Autor, 2015; Ugur et al., 2018).

Cost is evidently a factor in the adoption of digital technologies. This study aims to prove that human capital is more inexpensive than investments in technological advances. In emerging markets contexts, incremental advances in technology are more suitable than significant capital outlays and thus cost becomes a barrier of adoption.

2.6 Business Practice Differences between Regional Subsidiaries and Local Entities

International firms now place a lot of emphasis on the location of their regional subsidiaries in order to drive improved agglomerations (Arregle, Beamish, & Hébert, 2009). Key to the success of a foreign firm when operating in host countries is ensuring that statutory payments for operating in that host nation are minimal enough to enable competition with local competitors (Hsu, Chen, & Caskey, 2017). This implies that location is carefully researched before relocation.

The subsidiaries' financial performance is closely linked to the difference in regulations between the firm's home and host nation (Shirodkar & Konara, 2017). Research has concluded that there is an inverse relationship between the difference in regulations and the financial performance of subsidiaries. Local entities are immune to this. Furthermore, a standardization of business practices across subsidiaries in foreign owned firms would make the firm less agile in the adoption of new practices (Edwards, Sánchez-Mangas, Jalette, Lavelle, & Minbaeva, 2016).

2.7 Frontier Markets

Frontier markets are not widely discussed in academic literature. Their origin dates back to a term coined in 1992 by Farida Khambata that was used to define countries which are relatively more developed than the least developing markets but are still generally too small to be considered as emerging markets. Although there is no unanimously accepted definition or classification, they typically refer to countries that exhibit less maturity due to their demographic, developmental, political and liquidity dynamics (Wall, 2018). Multiple indices have varying interpretations of how to classify nations as either emerging or frontier, but one common criteria shared among the indices is the development of that particular nation's stock exchange. Additional criteria utilised to describe frontier markets include fairly developed financial sectors, modest macroeconomic growth and integrated capital growth due to evidence of constant foreign direct investment (Banya & Biekpe, 2018). Contrastingly, additional characteristics of some frontier markets include political instability and decaying levels of corporate governance (Guney, Kallinterakis, & Komba, 2017). However, these frontier markets still attract foreign direct investments due to the real return on yields that are on offer as a significant risk reward. Most of the frontier markets have varying levels of infrastructure development, but still attract investments from Multi-National Companies (MNC) due to the upside in returns that they can generate. Due to the difference in dynamics compared to the regions they emanate from, most MNC's need to tailor their market penetration and develop strategies according to the regional context. Research has shown, however, that offshore investment has surged recently despite the perceived lack of knowledge and adverse business operating dynamics, due to exponentially higher real yields of return compared to their originating regions (Quisenberry & Griffith, 2010).

2.8 Conclusion

In conclusion, this section discussed the concept of emerging technologies, in particular, artificial intelligence. The researcher discussed the impact artificial intelligence may have on the service. A brief discussion on the impact digital technologies have on the workforce was noted. The literature review was concluded with an examination of the prevalent factors that may influence the adoption of artificial intelligence and the readiness of employees to adapt to it. The specific factors are organisation leadership clarity, skill levels of employees, the cost of implementing these technologies, employee attitude during times of change and finally general access to the internet. The study will explore the strength of these factors further.

CHAPTER 3:
RESEARCH OBJECTIVES

3.1 Introduction

The objective of the research was to identify and understand the factors that may influence employee readiness to adopt and adapt to artificial intelligence within the context of the financial sector in Zambia. AI is a vehement topic that receives significant coverage. Additionally, most firms specialising in the provision of financial services place significant strategic emphasis on the importance of having digital objectives. However, the researcher did not find any literature that denoted that any research had been done on the driving forces of artificial intelligence in a developing markets context.

The researcher being of the belief that the study was somewhat under researched in a developing markets context, decided to address this gap in literature by conducting this research study. The following research questions were developed subsequent to a comprehensive literature review in order to test the strength of each factor in determining the adoption of artificial intelligence;

3.2 Research Question One

Does the level of organisational leadership clarity impact on the adoption of artificial intelligence in the Zambian banking industry.

Available literature does acknowledge the significant role of organisational management in the adoption of technologies (Alos-Simo et al., 2017; Bennis, 2013; Li et al., 2016; Turel & Bart, 2014). Further research has drawn conclusions of the extent to which managerial capabilities can accelerate or hinder the development of a digital strategy. This study will aim to understand the role organisational leadership clarity plays in the adoption of artificial intelligence in frontier markets.

3.3 Research Question Two

Does the skill levels of employees' impact on the adoption of artificial intelligence in the Zambian banking industry?

The emergence of technology such as automation was swiftly accompanied by rampant panic fuelled by fears of extensive job losses (Frey & Osborne, 2017). Alternative schools of thought diluted the job displacement effect of technology by offering an alternate view that the emergence of technologies actually had a more complementary effect on jobs (Arntz et al., 2017; Autor, 2015). This theory necessitated the need for the workforce to upgrade their complementary capabilities in terms of skill premiums in order to adapt to new job designs (Brynjolfsson & McElheran, 2016). This study aims to understand the impact employee skill levels has on the adoption of artificial intelligence in frontier markets.

3.4 Research Question Three

Does employee's attitude to organisational change impact the adoption of artificial intelligence in the Zambian banking industry?

Rafferty & Jimmieson (2017) argue that the frequency and magnitude of organisational change are significant predictors of an employee's resistance to embrace that change initiative. Technological change is perceived to be frequent and has the ability to effect incremental changes at organisational level (Yeo & Marquardt, 2015). This study aims to understand the impact that employee attitude to change has on the adoption of artificial intelligence the banking industry in Frontier markets.

3.5 Research Question Four

Does the general population's access to internet impact the adoption of artificial intelligence?

Advances in technological developments do not diffuse to the majority of the population in middle to low income countries due to the existence prevalent digital divides (Haenssgen, 2018). These digital inequalities are exacerbated by the high costs of reliable broad band internet (Robinson et al., 2015). This study aims to understand the impact the access to internet has on the adoption of artificial intelligence in the banking industry in Frontier markets.

3.6 Research Question Five

Does the cost of implementing new digital technologies impact the adoption of artificial intelligence?

The cost of implementing new technologies is a recurring theme in existing literature (Dyerson et al., 2016; Haug et al., 2011). The arguably slower pace of technological change in developing nations entails that wages for workers in these economies are lower than their counterparts in developed nations (Ugur & Mitra, 2017). This would imply that organisations may be more inclined to resist investing in digital technologies due to the fact that human is a cheaper alternative. This research study aims to understand the impact that the cost of implementing digital technologies has on the adoption of artificial intelligence.

The methodology that was utilised to answer the preceding research questions is detailed in the subsequent section of the document.

CHAPTER 4:
RESEARCH METHODOLOGY AND DESIGN

4.1 Introduction

The research intended to understand the factors that may influence the rate of adoption of artificial intelligence in frontier markets. The researcher, being a Zambian resident and being employed in the Zambian banking industry, utilised the Zambian financial sector as a case study to explore this phenomenon. The financial sector is a significant proponent of the use of digital technologies and AI is an emerging popular trend with its capacity for machine learning and the analysis of big data. The choice of research design is largely dependent on what information is sought from the study and if the collected data will provide the relevant information (Malhotra & Birks, 2007).

The study was conducted at Stanbic Bank Zambia Limited. The Zambian banking industry currently consists of 19 registered commercial banks (Bank Of Zambia, 2017). Stanbic Bank Zambia is a relatively significant player in the sector and is wholly owned by the Standard Bank of South Africa. For the last five years, Stanbic Bank Zambia has achieved after taxation income figures that place it in the top four banks consistently. Additionally, Stanbic Bank Zambia is one of the top banks in terms of market capitalization. Stanbic Bank Zambia is headquartered in Lusaka, which is the financial capital of Zambia.

A descriptive research design is one where a pre-formulated set of questions is asked to a pre-determined sample audience, in a pre-established sequence (Sreejesh, Mohapatra, & Anusree, 2014). The survey method of gathering data is ideal when dealing with a large number of respondents and is cost effective (Saunders & Lewis, 2012). The researcher's aim was to acquire 200 respondents or more, and the survey method seemed the most ideal.

The research was conducted as a deductive study on the Zambian banking industry to understand employee readiness to adopt artificial intelligence. Globally, the banking industry has implemented digital technologies, the purpose of the study is to understand if employees in the industry can adapt to the emerging technologies.

4.2 Philosophy

Research philosophy is a widely utilised research term that relates to the manner in which knowledge regarding a phenomenon is gathered and analysed in relation to research (Saunders & Lewis, 2012). This research study was grounded in a positive philosophy. A philosophy driven by a positivism approach aims to study observable behaviour and measurable variables in a controlled environment (Saunders & Lewis, 2012). The research aimed to identify factors that can influence the adoption of artificial intelligence. These are measurable variables that can be observed in a controlled environment. Saunders and Lewis (2012) also emphasize that the cause and effect aspect plays a pivotal role in a positivist philosophy. The researcher believes, a study that identifies factors that may serve as barriers or accelerators to the process has significant elements of cause and effect.

4.3 Approach

The study was deductive and quantitative in nature. A deductive research approach requires one to initially construct the research objectives from existing literature and answer these objectives from data that has been gathered as part of the research process (Malhotra & Birks, 2007). This study is not seeking to develop theory, but rather it intends to build on existing theory, by developing a model as a research outcome that can be replicated in similar regions and industries. Therefore, the deductive approach is the most appropriate. The research objectives were addressed through a quantitative study administered through an electronic survey. The electronic survey was administered via the SurveyMonkey™ tool to a sample of Stanbic Bank Zambia employees. The choice of methodology for this particular study was the mono method. Information was obtained through an electronic survey administered to a sample of employees in the named bank in the Zambian financial sector. This is common for quantitative studies.

4.4 Purpose of Research Design

A comprehensive review of literature was undertaken in order to frame the study's research objectives. The purpose of this research was to identify the factors that influence the adoption of artificial intelligence in frontier markets, in order to understand employee readiness to adapt. The research questions were framed after an extensive analysis of existing literature in order to determine the factors that act as barriers to artificial intelligence adoption so that their relevance in a frontier markets context could be assessed. Thereafter, a questionnaire was designed and administered to a sample of employees to gain further insights on the strength of the constructs that influence the pace of adoption of artificial intelligence in frontier markets. This was a deductive study as the research sought to gain further understanding of the phenomenon (Saunders & Lewis, 2012).

4.5 Time Horizon

Due to the time constraints that were prevalent during the study, a cross-sectional time horizon was utilised. Prior research has utilised longitudinal data extensively (Autor, 2015; Autor & Dorn, 2013; Frey & Osborne, 2017; Kristal, 2013) to assess the impact of various digital technologies on the workforce. However, the focus of this research is not to map out differences over a specific time period, but rather to gain a current understanding of the topic, through the collection of data during a single point in time, therefore a cross-sectional time horizon was the most suitable for this research (Zikmund, Babin, Carr, & Griffin, 2010)

4.6 Population

Saunders and Lewis (2012) define the population as a complete set of group members. The target population for this particular research was all financial services employees that face some form of technological change in frontier economies.

4.7 Units of Analysis

The units of analysis are the objects that the research is focused on. This research defined the units of analysis as the employees of all banks that operate in Zambia. Currently, there are 19 registered commercial banks in Zambia (Bank Of Zambia, 2017). Specifically, all staff members who have some form of interaction with artificial intelligence and are currently employed by Stanbic Bank Zambia Limited were targeted.

4.8 Sampling Method and Size

Saunders and Lewis (2012) define a sample as a subgroup of the population. The researcher earlier stated that the population of this research study was all financial services employees that face some form of technological change in frontier economies It is impractical to collect data from the entire population. Additionally, time and financial constraints will prevent one from doing so, hence the relevance of a well-defined sample (Saunders & Lewis, 2012). A possible limitation of sampling could be that the elements in one’s population are incomplete.

That is to say that one may not have received the complete list of individuals that constitute their population. A sampling frame is the exhaustive list of all elements of the population (Saunders & Lewis, 2012). For a sampling method to be accurate, the sampling frame requires accuracy as well. The researcher's sampling frame was a comprehensive list of all members of staff currently employed by Stanbic Bank Zambia. The purpose of this research was to build on theory by creating a model that can be replicated in similar industries. Convenient sampling is a form of sampling, where the sample is conveniently derived by the researcher (Zikmund et al., 2010). The sampling was determined using a defensible sampling method. This is a form of non-probability purposive sampling. The researcher sought to select a homogenous sample to try to minimize variations in the collected data. Non-probability convenience sampling is used primarily when the researcher utilises their own judgement to select a sample from the population (Saunders & Lewis, 2012). The researcher, being an employee of Stanbic Bank was acutely aware of which target respondents will be affected by any developments in artificial intelligence. Therefore, a convenience stratified sampling method was utilised. A manifest of employees was obtained from the Human Resource department of the bank, and respondents were selected from each business unit, as the researcher deemed this the most manner to achieve a representative sample of the bank. The researcher was confident that the sampling method was the most appropriate and would not hinder any further data analysis or interpretation thereof (McLaughlin, Dean, Mumper, Blouin, & Roth, 2013). The researcher anticipated restricted access to sampling units by other financial institutions due to confidentiality concerns and this formed the basis of motivation for the choice of the sampling strategy. The entire staff complement of Stanbic Bank Zambia currently sits at 696. Prior approval from the Human Capital department of Stanbic Bank to collect data was sought prior to designing the questionnaire. The approval letter can be sighted in the appendices. The self-administered questionnaire was designed using the SurveyMonkey™ tool and a secure link to access the survey was sent to a total of 365 respondents. A total number of 208 respondents completed the questionnaire, equalling a response rate of 56.99%. The ideal benchmark response rate for questionnaires targeted at organisation representatives ranges from 35% to 40% (Baruch & Holtom, 2008). Therefore, the response rate of 56.99% was adequate.

4.9 Measurement Instrument

The research objectives were framed from a comprehensive literature review to determine factors that influence the pace of artificial intelligence adoption. The factors retrieved from the literature review formed the basis of the constructs utilised to frame the core of the self-administered questionnaire. The research objectives are used to understand the existence of any barriers to artificial intelligence adoption in the banking sector, therefore, the questionnaire design intended to measure the strength and existence of those constructs. Questionnaires are ideal when collecting similar data from a large number of respondents (Zikmund et al., 2010). The benefits of using an online survey include the ease of administering the survey and the analysis of the collected data, which also includes increased levels of confidentiality perception by the respondents (Malhotra & Birks, 2007). A standard questionnaire was utilised and it employed the use of a seven point Likert scale to collect categorical data in order to explore the strength of these constructs. Likert scales are psychometric, non-comparative scales commonly used to measure attitudes (Malhotra & Birks, 2007). The survey was English based, online, self-administered questionnaire. The demographic data that was collected was descriptive, while the categorical data collected to measure the constructs was ordinal data (Saunders & Lewis, 2012).

The questionnaire was divided into sections. The first part of the questionnaire included seven demographic questions used to describe the target population. The demographic questions were intended to capture adequate descriptive demographic information that could be used to describe the population. All seven questions were posed in a way that respondents would select the answer that was most relevant to them from a pre-determined list of options. The second part of the questionnaire included fixed alternative questions that requested responses based on a seven point Likert scale (Malhotra & Birks, 2007). The constructs unearthed during the comprehensive literature review in Chapter 2 formed the basis of the questionnaire design. The respondents were requested to give feedback of their views of the various constructs on a scale that ranged from 1 (strongly agree) to 7 (strongly disagree). The constructs being investigated in the second half of the questionnaire are as follows;

1. Artificial Intelligence Adoption (the dependent variable)
2. Employee Attitude to Change
3. Skill Levels Gap
4. Leadership Clarity
5. Population Access to Technology
6. Cost of Implementation

The organisational leadership clarity questions were adapted from Turel & Bart (2014). The questions were adapted to fit the context of the study and simplified further post the pretesting phase. The employee skill level construct questions were built using the conclusions derived in research by Brynjolfsson & McElheran (2016) and Lyytinen & Grover (2017). Suppositions were derived, and questions constructed thereafter. The Employee attitude questions were constructed with the aid of the Technology Readiness Index scale developed by Parasuraman

(2000). The population access to internet construct questions were adapted from the framework developed by Haenssgen (2018). The cost of implementation construct questions were adapted from frameworks developed by Dyerson, Spinelli & Harindrath (2016) and Haug, Graungaard Pedersen & Arlbjørn (2011).

Saunders and Lewis (2012) stated that ethical concerns should be addressed in order to protect respondents' welfare. In that regard, a cover letter which spelt out the purpose of the research and informed participants of the confidential and voluntary nature of the survey preceded the questionnaire. A copy of the electronic survey is in Appendix A.

There must be significant consideration to ensure that the questions in the survey will not be misinterpreted by the respondents and will answer the research objectives. This is referred to as content validity in research (Saunders & Lewis, 2012). Validity refers to the measurement instrument's ability to produce relevant results to the research study (Sreejesh et al., 2014). To ensure content validity, special care was taken to ensure that the questions were worded accurately and were simple in order to extract the relevant data from the participants. In addition, due to the researcher being employed by the bank in question, it was prudent for the predetermined questions to be free of any bias. To eliminate bias, pilot questionnaires were undertaken by a total of 10 non-banking professionals in the initial testing phase. These measures ensured that the collected data has appropriate content validity (Saunders & Lewis, 2012). The feedback received required an adjustment of the questions posed in terms of quantity and additionally, some questions were not clear enough. The questions were reduced from a total of 45 to 30 after feedback from the initial pilot test revealed that the survey was too long and there was a risk of participants not completing it. Additionally, a few questions were excluded after feedback revealed that they were too ambiguous. The second round of testing involved sending the questionnaire to eight employees from competitor banks, who the researcher has a working relationship with. Six of the eight intended participants in the second round of testing responded and the feedback received was generally positive, citing that the questions were simple enough to comprehend and lacked ambiguity.

The term validity is referred to in research as the extent to which data collection methods accurately measure what they were intended to measure (Saunders & Lewis, 2012). The research objective was to understand the readiness of banking industry employee to adopt artificial intelligence adoption in frontier markets. The researcher was confident that a well-designed questionnaire would be adequate to measure the study's constructs. Of concern, however, is that some participants may not answer the questionnaire completely, or may not comprehend some of the questions and may answer incorrectly. In this case, special care should be taken to ensure that the questions posed are as simple as possible. Construct validity refers "*to the degree to which a measurement instrument represents and logically connects through the underlying theory*"(Sreejesh et al., 2014, p.117). Although this is not determined by the researcher, it must be taken note of. This was addressed during the two rounds of pre-testing and quality assurance checks.

The term reliability in research refers to the extent to which data collection methods and subsequent analyses will produce consistent findings (Saunders & Lewis, 2012). The scope of this research was to identify factors that could impact the adoption of artificial intelligence in a frontier markets context. This will aid in identifying factors that influence artificial intelligence adoption. A poorly designed questionnaire can lead to low data reliability. Administering the same electronic survey to all respondents can help combat this. Additionally, the researcher ensured simplicity in the questions posed in order for all respondents to comprehend them thoroughly by subjecting the survey to pre-testing. This should ensure consistent findings.

4.10 Data Gathering Process

A comprehensive literature review to identify factors and assess their relevance and impact on the workforce was undertaken. The questionnaire was developed as guided by the literature. Ethical clearance was sought from the Head of Human Capital at Stanbic Bank Zambia Ltd, to allow for the collection of data from employees. A copy of the approval letter from the bank can be found in the appendices. Subsequent to the development of the questionnaire, a link to the online version of the questionnaire was sent via email to 365 respondents. The data collection occurred from the 03rd of September 2018 to the 22nd of September 2018, allowing a three week period of data collection. A total of 215 people initially accessed the electronic survey, however eventually, 208 completed the survey, representing a 56.99% completion rate.

4.11 Analysis Approach

The completed questionnaire data was extracted and downloaded onto a Microsoft Excel file from SurveyMonkey™. The quantitative data was then analysed with the aid of a statistical analysis tool. For this research study, the Statistical Package for Social Sciences (SPSS™) was used to complete the analysis of the data. Prior to analysing the data, data had to be prepared in terms of coding and cleaning in order to increase the accuracy of the data (Pallant, 2010). A codebook in Excel was then designed to define and label all variables from the questionnaire and additionally to assign numerical values from 1 to 7 for all the responses. Subsequently, the data in the Excel spreadsheet was reviewed for any missing data (i.e. certain questions that were not responded to by participants). A total of 19 questions had not been responded to from a total of 11 participants. However, the selected confidence level for this particular study was 95%, implying an allowable 5% margin of error (Zikmund, Babin, Carr & Griffin, 2010). Following that rule, as long as less than 5% of the survey had not been answered by that particular respondent, then the respondent was included in the study. To ensure validity of the data, the missing data was subsequently replaced by the median score for that particular question. This process of sanitization reduced the number of viable respondents from the initial 208 to 198.

4.11.1 Use of Standard Deviation to Clean Data

The demographic data which contained nominal data was then excluded in order to further sanitise the data. For the purposes of a quantitative study, one requires variance in the data collected (Pallant, 2010). A standard deviation figure of 0.50 is deemed an acceptable variance in data and anything below that should be excluded from the data set (Pallant, 2010). Any standard deviation figure above 0.50 was deemed to have acceptable variance.

4.11.2 Mahalanobis Analysis

Further sanitization of the data required that the data be checked for normality in order to exclude any additional outliers. Pallant (2010) defines outliers as cases that have a standard residual of more than 3.3 and less than -3.3. The normality of a sample is measured using the Mahalanobis distance. In order to accurately measure the distribution of the data, the skewness and kurtosis of the data will need to be measured. The skewness value measures the distribution symmetry and the kurtosis value measures the peakedness of the distribution (Pallant, 2010). A Mahalanobis check revealed a few more outliers, who were excluded and the sample size once fully sanitized was at 185, equalling a 50.86% of the sample, which is still deemed acceptable.

4.11.3 Principle Component Analysis

The purpose of the study is to determine what factors influence the adoption of artificial intelligence in frontier markets. To achieve this, an exploratory factor analysis and confirmatory factor analysis were undertaken. Initially, to confirm the existence of the factors, a Kaiser Meyler Oklin Sampling Test was done. Values above 0.7 are considered reasonable and signify the factors' existence (Pallant, 2010). Thereafter, the Bartlett's Test of Sphericity was run and for a factor analysis to be relevant the p-value must be less than 0.05 (Pallant, 2010). Additionally, a Catell's Scree Test was plotted to verify the factors' existence. One limitation of principle component analysis, is that it assumes linearity in the components being analysed. This was addressed by running linearity tests, and the criteria for linearity was met. This process is discussed further in the subsequent section.

4.11.4 Multiple Regression

Post the exploratory and confirmatory factor analysis, a structural model was formulated. Once a model fit was confirmed, linearity which is a pre requisite for any regression model needs to be proven. Once the criteria for linearity was met, all standard multiple regression tests were conducted in order to determine the unique relationship each independent variable made in the prediction of the dependent variable, which was artificial intelligence adoption. Limitations can arise when conducting multiple regression analysis if data being analysed is incomplete. The researcher addressed this through multiple stages of data sanitizing and the exclusion of outliers from the data set.

4.12 Limitations

The proposed research design may introduce some limitations in the course of conducting the study. Firstly, the sample of the research is he workforce of one of the 19 banks in the Zambian financial sector. This may mean the data will not be fully representative of the target population.

Additionally, the researcher being employed by the bank may exhibit some bias in the questionnaire design, which could lead to low reliability in the data collection. Furthermore, there is a high chance of a large number of respondents not completing the questionnaire due to time constraints attributable to their workloads. In addition to that, some respondents may not be able to answer the survey due to inaccessibility of a computer, or lack of adequate bandwidth to access the site.

Finally, the use of convenience, non-probability sampling may exclude some staff members who may add valuable insights. Additionally, the use of an electronic survey also means not as much detail will be collected (Saunders & Lewis, 2012).

4.13 Summary of the Research Methodology and Design

This chapter comprehensively explained the research methodology and design employed by the researcher in the finalisation of this research report. Additionally, the research objectives in relation to the research philosophy employed were also explained and furthermore, the choice of population, sample and unit of analysis were equally comprehensively explained and justified.

CHAPTER 5:
PRESENTATION OF RESULTS

5.1 Introduction

This chapter presents the results of the analysis performed on the collected data as detailed in the preceding methodology chapter. The chapter will commence with a general description of the characteristics of the utilised research sample using descriptive statistics. This will be followed by an in-depth presentation of the descriptive analysis on the theoretical constructs and finally, the chapter will be concluded with a presentation of the findings in the research objectives context.

5.2 Characteristics of the Sample

A hyperlink for the online survey was sent to 365 Stanbic Bank Zambia employees. As presented in the methodology section, a non-probability, convenience sampling method was employed by the researcher to determine which respondents would constitute the sample. A grand total of 215 individuals accessed the online questionnaire. However, only a total of 208 participants completed the online questionnaire. This response rate signified a final response rate of 56.99%, making it an acceptable response rate for surveys sent out to organisational representatives (Baruch & Holtom, 2008). The subsequent section of this research paper will present the demographic characteristics of the sample in terms of age, gender, nationality, tenure, job grade, employment status and finally participants' qualifications.

5.2.1 Age

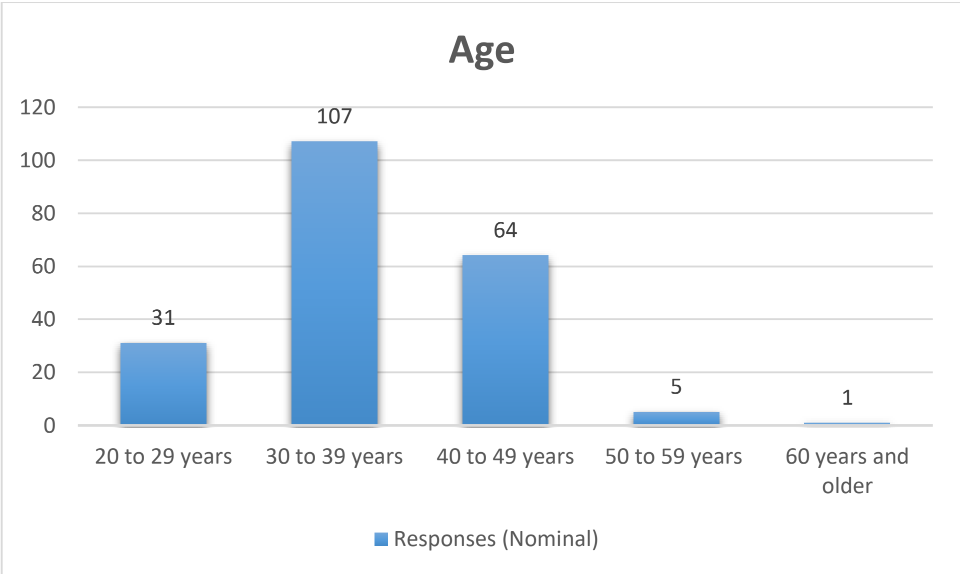
The age profile of the sample is depicted in the table below. The majority of the respondents were in the 30 to 39 year age grouping, with a resounding 51.44% of the respondents represented in that particular age bracket. The second highest number of respondents were located in the 40 to 49 year age bracket with a response rate of 30.77%.

Table 5. 1: Age Profile of Respondents

Category (Age)	Responses (Percentage)	Responses (Nominal)
20 to 29 years	14.90%	31
30 to 39 years	51.44%	107
40 to 49 years	30.77%	64
50 to 59 years	2.40%	5
60 years and older	0.48%	1

Below is a chart depicting the frequency distribution of the respondent's age brackets.

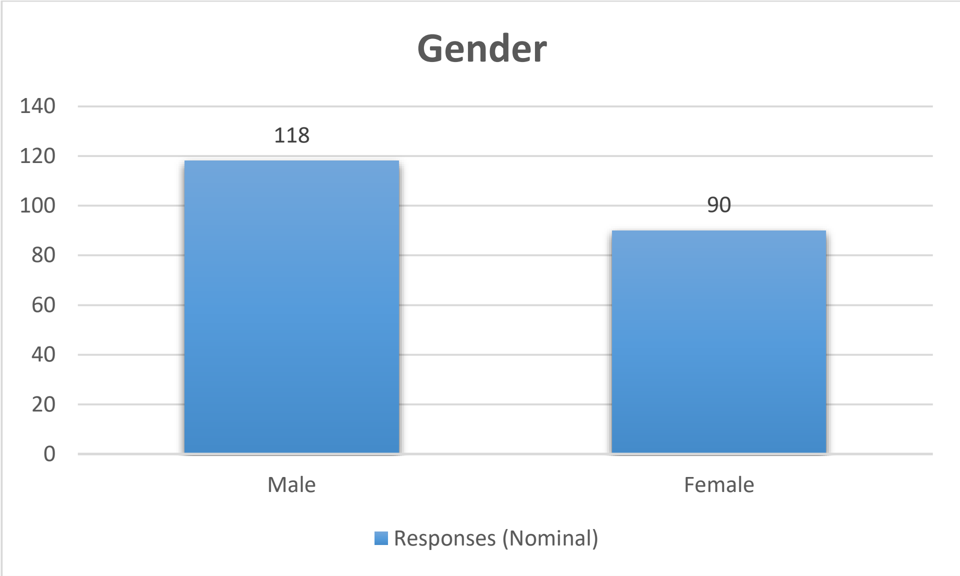
Figure 5.1: Frequency Distribution of Age Brackets



5.2.2 Gender

The majority of the respondents that participated in the survey were male. The response rate for males was 56.73%, while the remaining 43.27% were female. Zambian law does not have a provision for the population to identify themselves legally as anything other than male or female, so this option was not included in the measurement instrument. Below is a chart depicting the frequency distribution of the gender characteristics.

Figure 5.2: Frequency Distribution of Gender Groupings



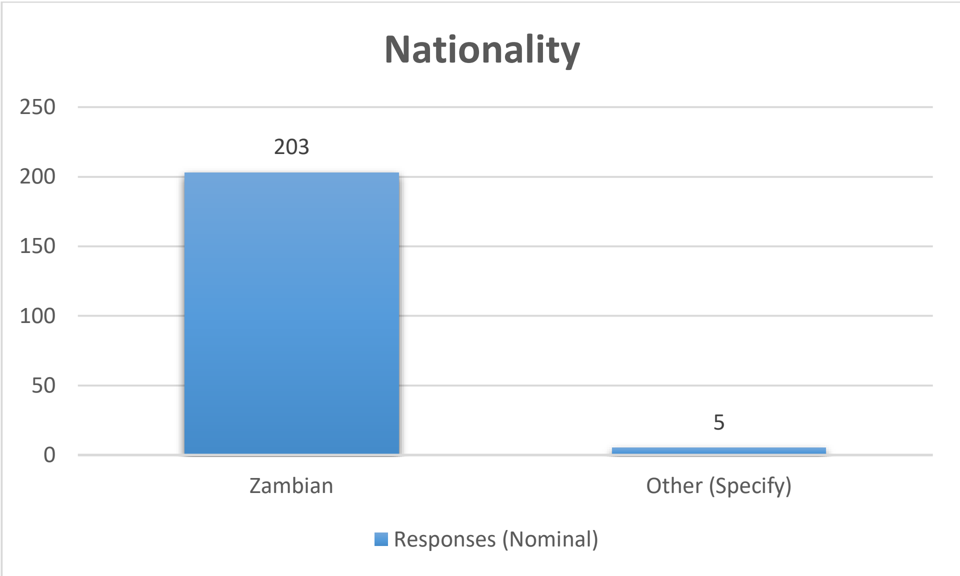
5.2.3 Nationality

The majority of the respondents that took part in the survey were Zambian. A resounding total of 97.60% of the respondents were Zambian, while 2.40% of the respondents were of nationalities other than Zambian. This was to be expected, as the survey was conducted in a Zambian bank, with a minority gathering of expatriate staff. The nationalities that comprised the other category included two South Africans, one Swati and one Kenyan. The final respondent neglected to specify their nationality. The following table and chart is a depiction of the nationality characteristics of the sample.

Table 5.2: Breakdown of Nationalities in Sample

Category (Nationality)	Responses (Percentage)	Responses (Nominal)
Zambian	97.60%	203
Other (Specify)	2.40%	5

Figure 5.3: Frequency Distribution of the Nationality Breakdown



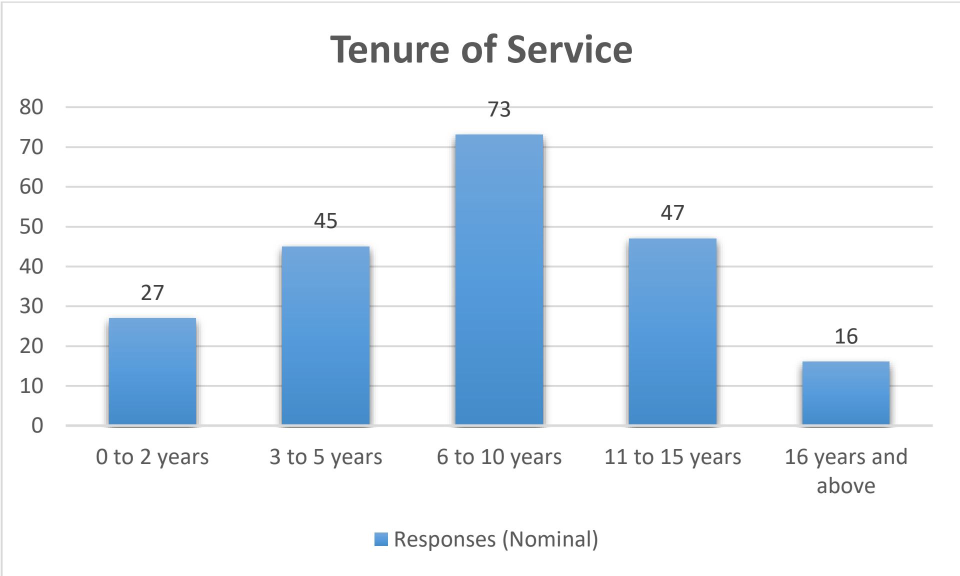
5.2.4 Tenure of Service

The majority of the respondents have a tenure of service to the bank of 6 to 10 years. The response rate for this particular respondent grouping was 35.10%. The second highest tenure of service was between 11 to 15 years, which had a response rate of 22.60%. It can, therefore, be implied that over half of the respondents (57.70%) have worked for the organisation for between 6 to 15 years. It is also interesting that the majority of the survey respondents were between 30 and 49 years of age, which is exactly 82.20% of the respondents. Another interesting aspect to note in this data is that only 12.98% of the respondents were between the ages of 20 to 29. This could signify that the bank does not have a lot of young staff members. The following table and chart presents the distribution of these tenure levels at the organisation.

Table 5.3: Tenure of Service at the Bank

Category (Length of Service)	Responses (Percentage)	Responses (Nominal)
0 to 2 years	12.98%	27
3 to 5 years	21.63%	45
6 to 10 years	35.10%	73
11 to 15 years	22.60%	47
16 years and above	7.69%	16

Figure 5.4: Frequency Distribution of Tenure of Service at Organisation



5.2.5 Job Grade

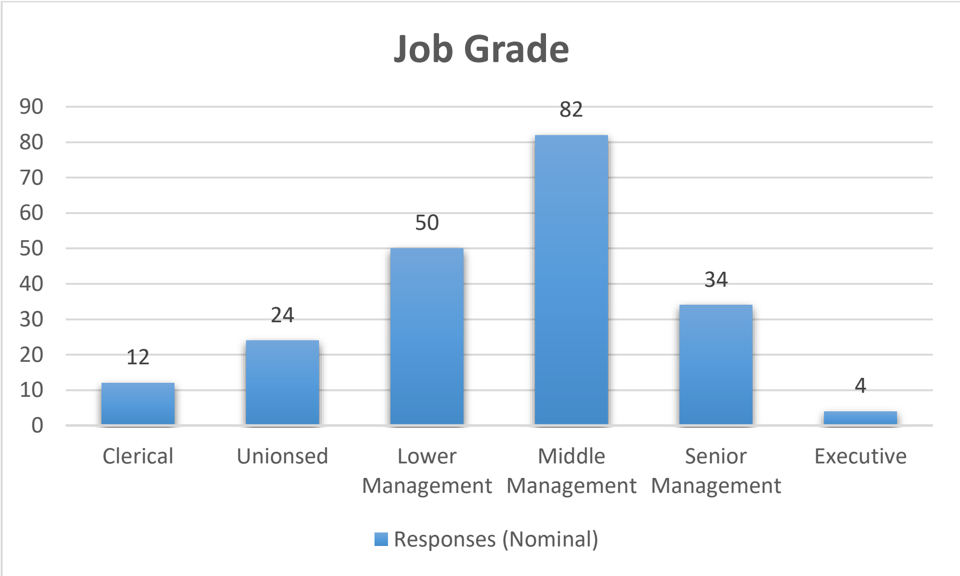
Respondents were requested to indicate their job grade. The majority of the respondents were in middle and lower management, with response rates of 39.81% and 24.27% respectively. This is interesting to note as if this could be tied back to the age bracket of the majority of respondents being in the 30 to 49 age bracket. Another interesting observation to make is that due to the majority of the respondents being in management, one could infer that they have some form of decision making leverage in the organisation. It may also be safe to infer that they would be rightly positioned to ascertain what factors can influence the adoption of artificial intelligence in their particular department, which can then be extrapolated to the banking sector and similar other industries. The table below depicts the variance in job grades among the respondents.

Table 5.4: Profile of Job Grades

Category (Job Grade)	Responses (Percentage)	Responses (Nominal)
Clerical	5.83%	12
Unionised	11.65%	24
Lower Management	24.27%	50
Middle Management	39.81%	82
Senior Management	16.50%	34
Executive	1.94%	4

Below is a graphical representation of the frequency distribution of the job grades.

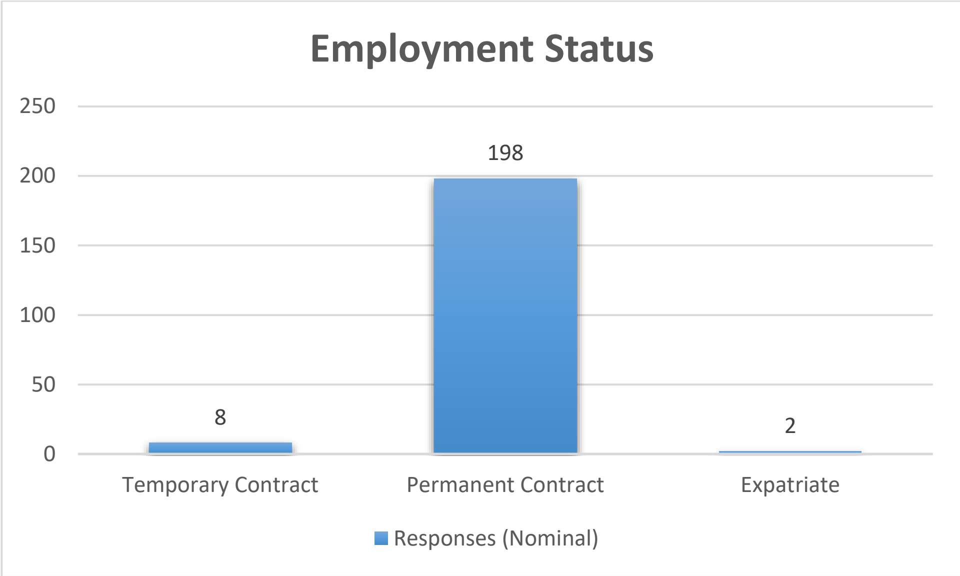
Figure 5.5: Frequency Distribution of Job Grade Classifications among the respondents



5.2.6 Employment Status

Respondents were further requested to indicate their employment status within the bank. The available employment options in the organisation were permanent, contractual and expatriate. Unsurprisingly, the majority of respondents were employed on a permanent basis with the bank and they had a response rate of 95.19%. Below is a graphical representation of the frequency distribution of the respondents' employment status.

Figure 5.6: Frequency Distribution of Employment Status of respondents



5.2.7 Qualifications

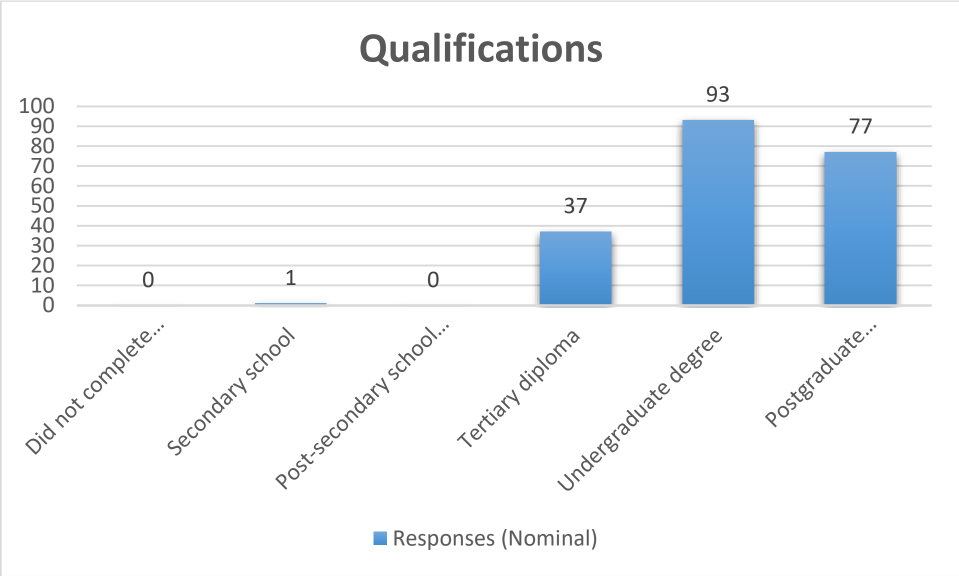
The majority of the respondents indicated that they had some form of post-secondary education. A total of 44.71% had undergraduate degrees, while a further 37.02% indicated that they had some form of post-graduate qualification as their highest form of education attained. Below is a table representing the qualification levels represented in the sample.

Table 5.5: Education Qualification Profile

Category (Qualifications)	Responses (Percentage)	Responses (Nominal)
Did not complete secondary school	0.00%	0
Secondary school	0.48%	1
Post-secondary school certificate	0.00%	0
Tertiary diploma	17.79%	37
Undergraduate degree	44.71%	93
Postgraduate qualification	37.02%	77

Below is a graphical representation of the educational qualifications of the sample

Figure 5.7: Frequency Distribution of Educational Qualifications of the sample



5.2.8 Correlations

Due to the fact that the collected data, had a normal distribution post sanitisation, a Pearson Correlation Test was run on the demographic variables in order to assess the strengths of the relationships between them. Below is a table depicting those correlations.

Table 5.6: Pearson's Correlation of Demographic Variables

		Age	Gender	Nationality	Length_of_service	Job_grade	Employment_status	Education
Age	Pearson Correlation	1	-0.119	0.043	.486**	.411**	.170*	0.001
	Sig. (2-tailed)		0.106	0.562	0.000	0.000	0.021	0.992
	N	185	185	185	185	185	185	185
Gender	Pearson Correlation	-0.119	1	0.036	0.024	0.009	0.107	0.005
	Sig. (2-tailed)	0.106		0.625	0.750	0.907	0.149	0.948
	N	185	185	185	185	185	185	185
Nationality	Pearson Correlation	0.043	0.036	1	-0.045	0.122	.229**	0.112
	Sig. (2-tailed)	0.562	0.625		0.539	0.099	0.002	0.129
	N	185	185	185	185	185	185	185
Length_of_service	Pearson Correlation	.486**	0.024	-0.045	1	.256**	0.057	-0.119
	Sig. (2-tailed)	0.000	0.750	0.539		0.000	0.437	0.107
	N	185	185	185	185	185	185	185
Job_grade	Pearson Correlation	.411**	0.009	0.122	.256**	1	.376**	.325**
	Sig. (2-tailed)	0.000	0.907	0.099	0.000		0.000	0.000
	N	185	185	185	185	185	185	185
Employment_status	Pearson Correlation	.170*	0.107	.229**	0.057	.376**	1	.226**
	Sig. (2-tailed)	0.021	0.149	0.002	0.437	0.000		0.002
	N	185	185	185	185	185	185	185
Education	Pearson Correlation	0.001	0.005	0.112	-0.119	.325**	.226**	1
	Sig. (2-tailed)	0.992	0.948	0.129	0.107	0.000	0.002	
	N	185	185	185	185	185	185	185

****. Correlation is significant at the 0.01 level (2-tailed).**

***. Correlation is significant at the 0.05 level (2-tailed).**

As presented in prior sections, there have been a few relationships that have been interesting to note which the positive correlations highlighted in the preceding table confirm. For instance, the job grade variable has a positive correlation at the 95% significance level with age, employment status, length of service and attained educational qualifications. It can be inferred from these statistics that, an individual's job grade has a positive correlation with their age, their educational qualifications, their length of service and their educational status with the organisation.

5.3 Exploratory Factor Analysis

The purpose of this study is to investigate what factors drive the employee readiness to adopt artificial intelligence in frontier markets. In this regard, the collected data should unpack the factors and determine the strength of the independent variables that include; employee attitude, cost, leadership clarity, population access to technology and skills gap have in driving the direction of the dependent variable and artificial intelligence readiness. In order to assess the factorability of the collected data, Pallant (2010) recommends the use of two statistical tests, which are the Bartlett's Test of Sphericity and the Kaiser-Meyer-Oklin Measure of Sampling Adequacy (KMO). For the factor analysis to be considered appropriate, the following conditions need to be met, Bartlett's Test should be significant, meaning the p-value should be less than 0.05 (Pallant, 2010). Additionally, the KMO index should be above 0.6 (Pallant, 2010). Rafferty and Jimmieson (2017) utilise a similar method to assess the suitability of factors in their study. The first table shown below depicts the descriptive statistics of the constructs variables and the subsequent tables then displays the KMO and Barlett's values.

Table 5.7: Descriptive Statistics of the Theoretical Construct Variables

Construct Variables	Mean	Std. Deviation	Analysis N
Artificial Intelligence Adoption (AI_1)	2.42	1.096	185
Artificial Intelligence Adoption (AI_2)	2.50	1.294	185
Artificial Intelligence Adoption (AI_3)	2.11	1.012	185
Artificial Intelligence Adoption (AI_4)	2.97	1.487	185
Employee Attitude to Change (EM_AT_1)	1.56	0.650	185
Employee Attitude to Change (EM_AT_2)	2.68	1.475	185
Employee Attitude to Change (EM_AT_3)	2.40	1.368	185
Employee Attitude to Change (EM_AT_4)	4.86	1.707	185
Skills Gap (SK_G_1)	1.52	0.572	185
Skills Gap (SK_G_2)	2.36	1.269	185
Skills Gap (SK_G_3)	1.57	0.596	185
Skills Gap (SK_G_4)	1.77	0.748	185
Leadership Clarity (LEAD_1)	2.24	1.015	185
Leadership Clarity (LEAD_2)	2.22	1.067	185
Leadership Clarity (LEAD_3)	2.47	1.133	185
Leadership Clarity (LEAD_4)	2.49	1.138	185
Population Access to Technology (POP_AT_1)	3.30	1.365	185
Population Access to Technology (POP_AT_2)	3.55	1.410	185
Population Access to Technology (POP_AT_3)	3.44	1.390	185
Cost of Implementation (COST_1)	1.19	0.423	185
Cost of Implementation (COST_2)	2.15	1.321	185
Cost of Implementation (COST_3)	2.46	1.532	185
Artificial Intelligence Adoption (AI_5)	0.34	0.473	185

Table 5.8: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**0.795**
Bartlett's Test of Sphericity	**Approx. Chi-Square**	1511.027
	df	253
	Sig.	**0.000**

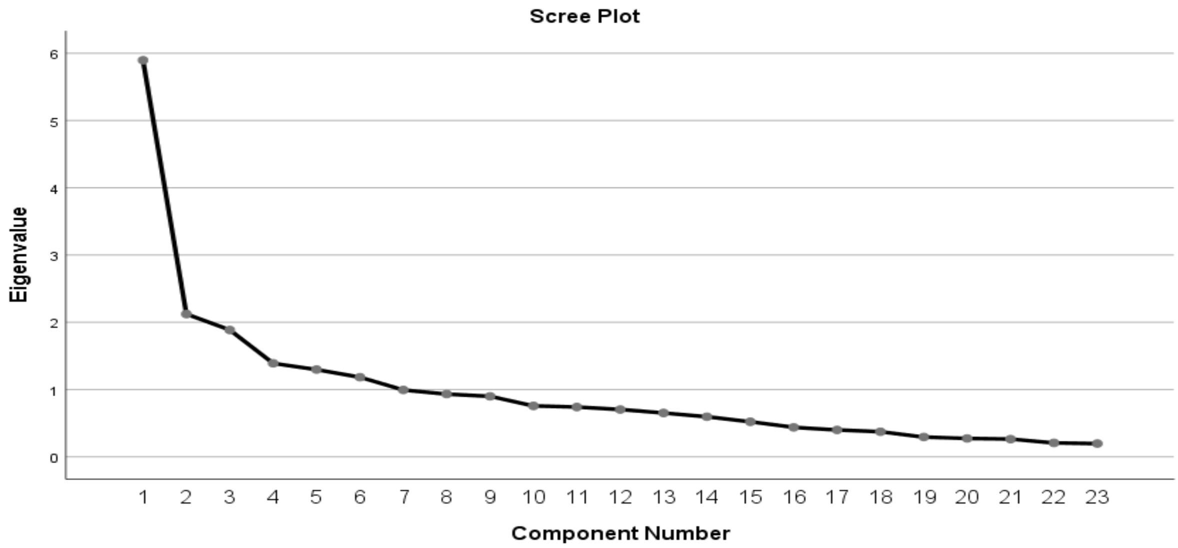
The tests revealed a KMO figure of 0.795, considering that any value above 0.60 is considered appropriate, this lets the researcher know that the factor analysis is appropriate. Additionally, using the Barltett's Test, the factor analysis is significant as the p-value is below 0.05. Based on these results, this means that a factor analysis can now be conducted.

Consequently, the data analysis now had to determine how many factors were prevalent. This process is referred to as factor extraction. This method involves determining the least amount of factors that can adequately explain the inter relationship of a set of variables (Pallant, 2010). Using Kaiser's criterion, any component that has an eigenvalue of 1 or more will qualify as a suitable factor to be analysed (Pallant, 2010). This was achieved through the analysis of the Total Variance Explained (TVE) table. In addition to that, a further factor extraction can be conducted using the scree plot. Below is a table showing the TVE values and a figure depicting the scree plot.

Table 5.9: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.896	25.636	25.636	5.896	25.636	25.636
2	2.122	9.227	34.863	2.122	9.227	34.863
3	1.885	8.198	43.061	1.885	8.198	43.061
4	1.390	6.042	49.103	1.390	6.042	49.103
5	1.297	5.639	54.741	1.297	5.639	54.741
6	1.183	5.144	59.885	1.183	5.144	59.885
7	0.993	4.317	64.203			
8	0.932	4.051	68.253			
9	0.899	3.909	72.162			
10	0.756	3.287	75.449			
11	0.739	3.214	78.663			
12	0.702	3.054	81.717			
13	0.651	2.829	84.546			
14	0.595	2.586	87.133			
15	0.520	2.262	89.394			
16	0.437	1.902	91.296			
17	0.399	1.735	93.031			
18	0.372	1.618	94.649			
19	0.293	1.275	95.923			
20	0.273	1.186	97.109			
21	0.263	1.142	98.251			
22	0.206	0.896	99.147			
23	0.196	0.853	100.000			

Figure 5.8: Screeplot



Upon completing the principal component analysis and utilising the TVE scores, any component with an eigenvalue of 1 or above is deemed accepted. From the above TVE table, it should be noted that six components were deemed to have eigen value of 1 and above. Interpreting this would mean that six factors have a cumulative 59.885% of the variance. In simpler terms, 59.885% of the variance in the research can be explained by six factors. This is further evidenced on the scree plot above with six factors all above the eigenvalue of 1. This signifies that these factors can be analysed. To aid in the interpretation of the six components, a varimax rotation was performed. The rotation was performed using Kaiser Normalization. The criteria in which the data was sorted was that all values greater than 0.4 remained part of the factor analysis, while the remainder of the data was excluded. Furthermore, one of the construct variables which measured artificial intelligence readiness did not have a coefficient value. The variable on the research instrument was posed as, “The organisation has a dedicated IT department with a variety of IT specialists who interact with all levels of the organisation regularly”. The significance of a lack of value means it contributes nothing to the structural model and it is too weak a variable to include, therefore, it was excluded. The exclusion of this variable improved the TVE cumulative percentage to 61.401% as evidenced in the table below.

Table 5.10: Total Variance Explained post-Varimax Rotation using Kaiser Normalization

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5.671	25.779	25.779	5.671	25.779	25.779	4.818
2	2.111	9.594	35.373	2.111	9.594	35.373	3.131
3	1.883	8.559	43.932	1.883	8.559	43.932	3.282
4	1.389	6.314	50.246	1.389	6.314	50.246	2.147
5	1.297	5.893	56.140	1.297	5.893	56.140	2.657
6	1.158	5.262	61.401	1.158	5.262	61.401	1.378

5.3.1 Reliability of Factor Analysis

The subsequent section will now assess the reliability of the factor analysis. A measure of reliability is internal consistency. This relates to the degree to which the items in the same scale are measuring the same attribute. The most commonly utilised method of measuring reliability is through the Cronbach's Coefficient Alpha, with a recommended minimum value of 0.7 (Pallant, 2010). The six factors were then tested for reliability utilising the Cronbach Alpha as a measure of reliability, below is a tabulation of the outcomes.

Table 5.11: Exploratory Factor Analysis Reliability Check

Construct	Cronbach's Alpha	Construct Variable	Mean	Std. Deviation	N
Leadership Clarity	0.870	LEAD_1. The organisation has a well-defined digital strategy	2.2378	1.0149	185
		LEAD_2. The organisation in terms of personnel and resources places considerable emphasis on the implementation of its digital strategy	2.2162	1.0667	185
		LEAD_3. The organisation is proactive in communicating any developments concerning digital or technological advances in the organisation	2.4703	1.1327	185
		LEAD_4. The organisation's leadership is effective at communicating the future benefits of implementing its digital strategy	2.4865	1.1378	185
		SK_G_2. The organisation provides adequate training on new systems and products before they are launched	2.3568	1.2693	185
		EM_AT_2. The organisation is proactive in communicating any changes before the change is implemented	2.6757	1.4754	185
Skills Gap	0.640	SK_G_1. I have the adequate skills for my current role at work	1.5243	0.5717	185
		SK_G_3. I am comfortable with the use of technology to help me do my job better	1.5676	0.5962	185
		SK_G_4. I use electronic platforms extensively and comfortably in my current role	1.7676	0.7482	185
		COST_1. New technology is necessary to keep the organisation competitive	1.1946	0.4235	185
		EM_AT_1. I have a positive attitude towards change in the organisation, and I always look forward to trying new things	1.5568	0.6496	185
		AI_1. Artificial intelligence as a concept is something I am fairly comfortable with	2.4216	1.0962	185
Population Access to Technology	0.812	POP_AT_1. Most of the organisation's clients have a good understanding of the bank's technology	3.3027	1.3654	185
		POP_AT_2. Most of the organisation's client's embrace all new technological products and services with ease	3.5459	1.4101	185
		POP_AT_3. Most of the organisation's electronic platforms are extensively used by the bank's clients	3.4432	1.3903	185
Cost of Implementation	0.779	COST_2. The organisation should upgrade their technology regularly, regardless of the cost	2.1459	1.3209	185
		COST_3. The cost of new technologies is insignificant compared to the benefits it may bring	2.4649	1.5323	185
Artificial Intelligence Adoption (Dependent Variable)	0.555	AI_2. The organisation uses a variety of sophisticated systems and software across the network	2.5027	1.2943	185
		AI_4. The organisation provides sophisticated software that makes the analytical part of my job easier	2.9730	1.4870	185
		AI_5. In your opinion, is the organisation proactive in keeping up to date with technological developments in the sector/industry?	0.3351	0.4733	185
Employee Attitude to change	0.334	EM_AT_3. Inadequately communicated adjustments in my job design make me anxious	2.4000	1.3681	185
		EM_AT_4. Technology will eventually replace my role in the workplace	4.8595	1.7073	185

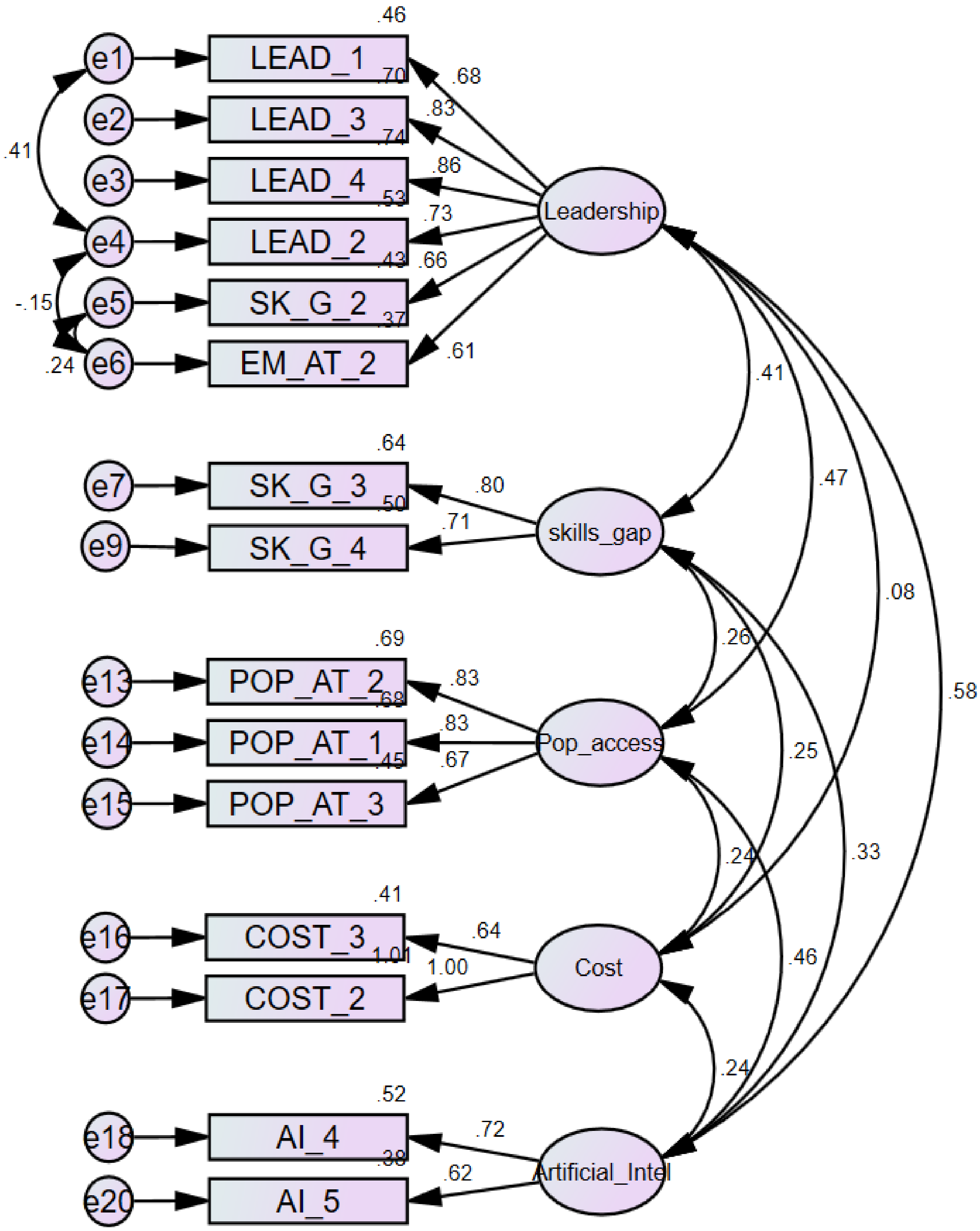
As stated earlier, a minimum Cronbach Alpha value of 0.7 is required for reliability to be present in a factor. The leadership clarity, population access to technology and the cost of implementation constructs all have good Cronbach Alpha coefficients at 0.870, 0.812, and

0.779 respectively. The skills gap construct has a Cronbach coefficient of 0.640, however, if we remove the construct variable AI-1 ("*Artificial intelligence as a concept is something I am fairly comfortable with*"), the Cronbach Alpha coefficient will improve to 0.705, therefore the factor is reliable once that construct variable is excluded. The AI adoption construct has a low Cronbach Alpha coefficient of 0.555 and exclusion of any of the construct variables improves it marginally to 0.561. There is a certain degree of concern regarding the reliability of this construct. The employee attitude to change construct has a cronbach coefficient of 0.334, which is poor. The statistical reliability of this construct is poor, and thus will be excluded from the measurement model. The factors suitable for analysis were reduced to five from the initial six.

5.3.2 Structural Equation Modelling

Structural equation modelling combines multiple regression techniques with factor analysis to study the relationship between variables (Tabachnick & Fidell, 2007). The purpose of conducting a structural equation model is to improve the model fit of the theoretical constructs post the exploratory factor analysis. The first step undertaken was to establish a measurement model, for this particular task, an additional statistical package called Analysis of Moment Structures, (AMOS$^{TM)}$ was utilised. It should be noted, however, that the measurement model does not distinguish between independent and dependent variables, but it is purely utilised in order to improve the model fit of the theoretical constructs (Tabachnick & Fidell, 2007). As stated earlier, a few of the construct variables derived from the factor analysis contained a few reliability and validity concerns. The establishment of a measurement model refines the model fit according to pre-set criteria. The purpose of a measurement model is to confirm that all constructs are giving you a model fit. A measurement model is a representation of the underlying theory that displays how the measured variables can be combined to represent constructs (Hair, Black, Babin, Barry, & Anderson, 2014). The initial measurement model contained some validity concerns. To correct this, construct variables with low factor loading were excluded from the final measurement model. A figure depicting the final measurement model is displayed below.

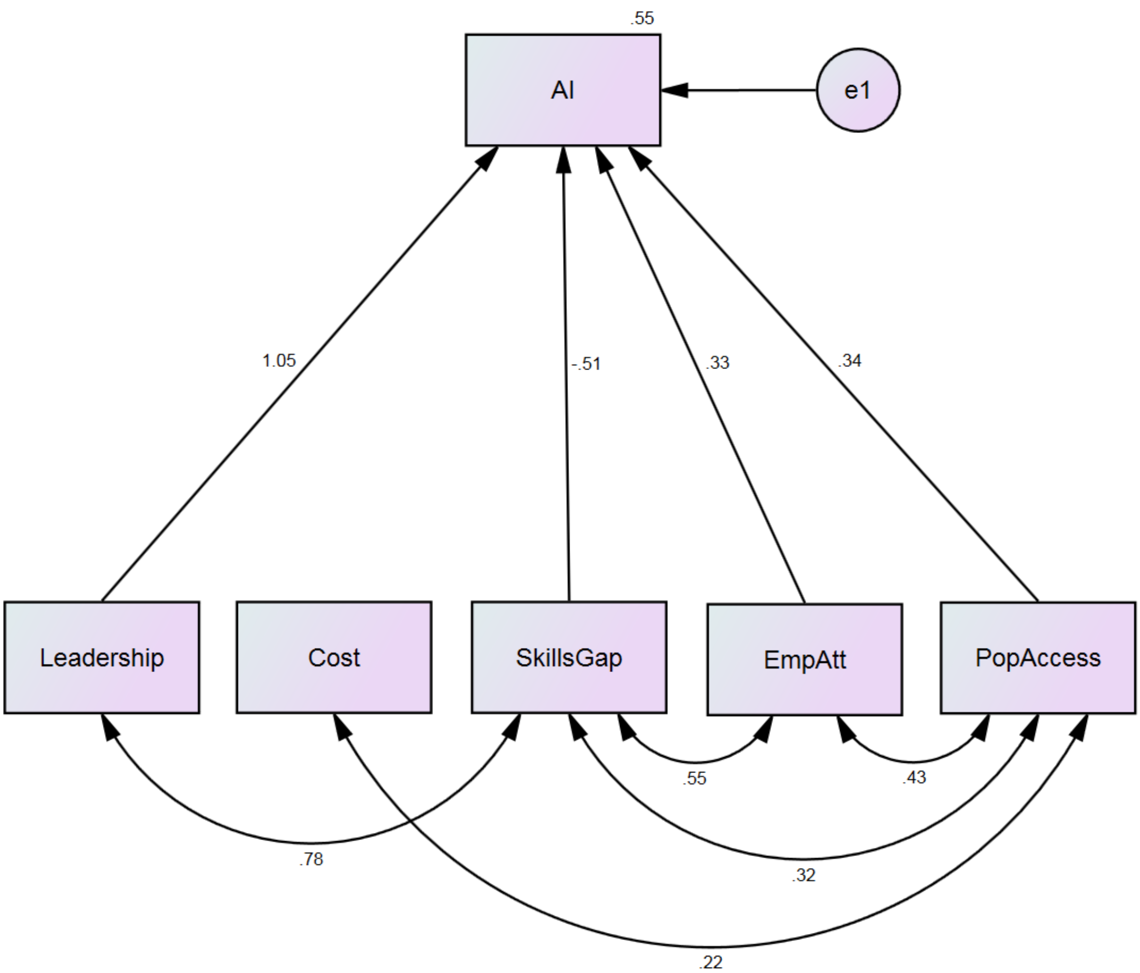
Figure 5.9: Standardised Final Measurement Model



The ‘p’ values for the regression weights post the measurement model for all five of the theoretical constructs are less than 0.001, thereby implying that they are significant. A tabulation of these regression weights in addition to the correlations between the constructs is displayed in the appendices. The establishment of this measurement model is further confirmation that the model has construct validity (Hair et al., 2014).

The model was further improved by establishing a structural model. A structural model further tests for validity and reliability of the constructs. The establishment of a structural model confirms how the separate constructs are related to one another through the use of multiple dependence relationships (Hair et al., 2014). While the measurement model measured the variables to factors, the structural model measures the hypothesized relationship between the constructs (Tabachnick & Fidell, 2007). Certain improvements to the model were achieved by the removal of further variables with low factor loading. There were certain indices that were below the set criteria, but the overall picture was a good model fit. The final simplified structural model is located below.

Figure 5.10: Simplified Structural Model – Standardised



5.3.3 Multiple Regression

For any regression model, linearity needs to be proven. A linearity test was conducted through a curve fit analysis and linearity for all constructs was established. For a regression model to meet the criteria of linearity, all F values should be within the same range. The following table shows the F values for the constructs.

Table 5.12: Model Summary (Construct F Values)

Dependent Variable:	Artificial Intelligence Adoption									
		Model Summary					Parameter Estimates			
Independent Variables	Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Cost Of Implementation	Linear	0.031	**5.863**	1	183	0.016	2.323	0.145		
Leadership Clarity	Linear	0.559	**231.521**	1	183	0.000	0.779	0.735		
Skills Gap	Linear	0.507	**188.539**	1	183	0.000	0.729	0.734		
Population Access to Technology	Linear	0.299	**78.222**	1	183	0.000	1.166	0.463		
Employee Attitude to Change	Linear	0.406	**125.271**	1	183	0.000	1.227	0.502		

All F values are within the same range apart for the one for the cost of implementation construct. The researcher had to relook at the correlations between the constructs to interpret this. The Durbin Watson Test was also conducted. The Durbin Watson Test measures the autocorrelation of errors, if significant is an indication of non independence of errors (Tabachnick & Fidell, 2007). A d-value of 1.749 indicated that there was no significant evidence of autocorrelation.

Subsequent to establishing the structural model in order to answer the research questions posed, correlation needs to be established between the various factors. There must be a strong correlation between the factors. Below is a table displaying the correlations between the constructs.

Table 5.13: Correlations between Constructs

		Cost of Implementation	Leadership Clarity	Skills Gap	Population Access to Technology	Employee Attitude to Change	Artificial Intelligence Adoption
Cost of Implementation	Pearson Correlation	1	0.073	0.115	.292**	.150*	.176*
	Sig. (2-tailed)		0.327	0.118	0.000	0.041	0.016
	N	185	185	185	185	185	185
Leadership Clarity	Pearson Correlation	0.073	1	.939**	.438**	.779**	.747**
	Sig. (2-tailed)	0.327		0.000	0.000	0.000	0.000
	N	185	185	185	185	185	185
Skills Gap	Pearson Correlation	0.115	.939**	1	.521**	.890**	.712**
	Sig. (2-tailed)	0.118	0.000		0.000	0.000	0.000
	N	185	185	185	185	185	185
Population Access to Technology	Pearson Correlation	.292**	.438**	.521**	1	.452**	.547**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000
	N	185	185	185	185	185	185
Employee Attitude to Change	Pearson Correlation	.150*	.779**	.890**	.452**	1	.637**
	Sig. (2-tailed)	0.041	0.000	0.000	0.000		0.000
	N	185	185	185	185	185	185
Artificial Intelligence Adoption	Pearson Correlation	.176*	.747**	.712**	.547**	.637**	1
	Sig. (2-tailed)	0.016	0.000	0.000	0.000	0.000	
	N	185	185	185	185	185	185

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Artificial intelligence adoption is the dependent variable. It can be noted that all independent variables have positive correlations at 99% confidence level, apart from the cost of implementation variable which has a weak positive correlation at 95% confidence with a p-value of 0.176. The leadership clarity variable has the strongest correlation with a p-value of 0.747, while the skills gap variable is equally as strong with a p-value of 0.712. The population access to technology and employee attitude to change additionally have positive correlations to the dependent variable with p values of 0.547 and 0.637 respectively. The independent variables have relatively positive correlations to each other, aside from the cost of implementation variable which only has weak positive correlations to the population access to technology variable and the employee attitude to change variables. Interesting to note, however, is that there is a significant positive correlation between the leadership clarity and the skills gap variables at a p-value of 0.939. This will be explored further in subsequent sections.

A multiple regression analysis was subsequently performed to determine the strength of relationships between the dependent variable, artificial intelligence adoption and the independent variables. The separate tables showing the individual regression models can be found in the appendices. All independent variables exhibited moderate to strong relationships with the dependent variable, with the leadership clarity variable exhibiting the strongest relationship with an R^2 value of 0.559, implying that 55.9% of the leadership clarity constructs is a predictor of the dependent variable artificial intelligence readiness. Below is a table showing the results of the regression analysis with all factors combined.

Table 5.14: Regression Model of Constructs

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.799[a]	0.639	0.629	0.55532	0.639	63.367	5	179	0.000	1.749

a. Predictors: (Constant), Employee Attitude, Cost, Population Access, Leadership, Skills Gap
b. Dependent Variable: Artificial Intelligence Adoption

The R^2 for the whole model is 0.639, while the regression model for the leadership clarity variable which is the strongest is 0.559. This implies that the model can be improved. To improve the model, collinearity of the variables will need to be investigated. The collinearity coefficients were analysed and it was discovered that the coefficient for the cost of implementation variable was not significant at a p-value of 0.333. This signifies that the cost of implementation variable did not contribute to the overall model and this was excluded. Every other independent variable was found to be significant at a 95% confidence level. To further address the multicollinearity in the model, the Variance Inflation Factors (VIF) were investigated. When multicollinearity exists, the variance of the estimated coefficients are inflated (Tabachnick & Fidell, 2007). The VIF is the factor by which the variance is inflated. Any VIF value above 10 will be a cause of concern, as it is evidence that multicollinearity exists (Pallant, 2010). Below is a tabulation of the coefficients to further illustrate the point.

Table 5.15: Collinearity Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	0.366	0.151		2.431	0.016	0.069	0.664		
	Cost	0.038	0.039	0.046	0.972	0.333	-0.039	0.115	0.900	1.111
	Leadership	0.925	0.141	0.941	6.579	0.000	0.647	1.202	0.099	10.140
	Skills Gap	-0.600	0.210	-0.582	-2.856	0.005	-1.014	-0.185	0.049	20.616
	Population Access	0.252	0.047	0.297	5.335	0.000	0.159	0.345	0.649	1.542
	Employee Attitude	0.222	0.084	0.282	2.633	0.009	0.056	0.389	0.176	5.696

The table above points out that both the leadership clarity and skills gap variables have VIF values above 10, which is evidence of collinearity. The researcher in a prior section pointed out that there was a strong correlation found between these two variables, therefore this finding was not surprising. It is an indication that the two variables may be measuring the same thing. The skills gap variable was then excluded from the model as it had a higher VIF value of 20.616. The removal of the skills gap variable reduced the leadership variable's VIF value to 2.636. This action equally altered the regression model's R^2 value to 0.623. To further improve the model, the collinearity coefficients were analysed post the removal of the skills gap variable. It was discovered that the collinearity coefficient for the cost and employee attitude variables were not significant with p values of 0.277 and 0.431 respectively, and the researcher excluded them from the final model. Once those two variables had been excluded, the final model demonstrates that the leadership and population access to technology variables are the predictors to the dependent variable artificial intelligence readiness. The beta value for the leadership variable in the regression model is 0.617 and the beta value for population access to technology is 0.230. Below is a tabulation of the final regression model from the collected data.

Table 5.16: Final Regression Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.786[a]	0.618	0.614	0.56625	0.618	147.439	2	182	0.000	1.842

a. Predictors: (Constant), Population Access, Leadership

b. Dependent Variable: Artificial Intelligence Adoption

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	0.351	0.144		2.432	0.016	0.066	0.636		
	Leadership	0.617	0.050	0.628	12.332	0.000	0.519	0.716	0.808	1.237
	Population Access	0.230	0.043	0.272	5.341	0.000	0.145	0.315	0.808	1.237

a. Dependent Variable: Artificial Intelligence Adoption

In conclusion, a multiple linear regression was calculated to predict artificial intelligence adoption based on leadership clarity and population access to technology. A significant regression equation was found. Results of the research study indicate that artificial intelligence is equal to **0.351 + 0.617(Leadership Clarity) + 0.230 (Population Access to Technology)**. The study further indicated that both the leadership clarity and population access to technology variables were significant predictors of the artificial intelligence adoption dependent variable.

5.4 Conclusion of Results

The collected data from the research study revealed interesting and somewhat unexpected insights into what is perceived as the ultimate driving forces of artificial intelligence adoption in frontier markets. The final regression model shows that organisational leadership clarity and demographic dynamics of the population which an entity is serving in terms of internet accessibility are the most significant drivers of artificial intelligence adoption. Variables such as skill levels of employees, cost of implementation and employee attitude were not deemed to be significant predictors of artificial intelligence adoption according to the collected data.

In conclusion, the obtained results had the following implications on the research questions that were tested;

Research Question One

Does the level of organisational leadership clarity impact on the adoption of artificial intelligence in the Zambian banking industry.

A Pearson correlation test was run to determine the correlation between organisational leadership clarity as an independent variable and artificial intelligence adoption as the dependent variable. The results of that Pearson Correlation test indicated that the relationship between the organisational leadership clarity independent variable and the artificial intelligence adoption dependent variable was significant at a 95% confidence level. The Pearson Correlation coefficient was 0.747, denoting a strong positive relationship between this independent variable and the dependent variable. The researcher can hereby conclude that due to the strong positive correlation, organisational leadership clarity does directly impact the adoption of artificial intelligence. Further to that, a multiple regression analysis was run and organization leadership clarity was found to be a significant predictor of artificial intelligence adoption.

Research Question Two

Does the skill levels of employees' impact on the adoption of artificial intelligence in the Zambian banking industry?

A Pearson correlation test was run to determine the correlation between employee skills level as an independent variable and artificial intelligence adoption as the dependent variable. The results of that Pearson Correlation test indicated that the relationship between the skills level independent variable and the artificial intelligence adoption dependent variable was significant at a 95% confidence level. The Pearson Correlation coefficient was 0.712, denoting a strong positive relationship between this independent variable and the dependent variable. The researcher can hereby conclude that due to the strong positive correlation, employee skill levels as a variable does positively impact the adoption of artificial intelligence. Further to that a multiple regression analysis was run where a multi collinearity issue was discovered between the employee skills level variable and the organisational leadership clarity variable. The employee skill level variable had a higher VIF figure and was thus excluded from the final regression model. The researcher can then conclude while employee skill levels are strongly positively correlated to artificial intelligence adoption, it is not a significant driver of the phenomenon.

Research Question Three

Does employee's attitude to organisational change impact the adoption of artificial intelligence in the Zambian banking industry?

A Pearson correlation test was run to determine the correlation between employee attitude to change as an independent variable and artificial intelligence adoption as the dependent variable. The results of that Pearson Correlation test indicated that the relationship between the employee attitude to change independent variable and the artificial intelligence adoption dependent variable was significant at a 95% confidence level. The Pearson Correlation coefficient was 0.637, denoting a strong positive relationship between this independent variable and the dependent variable. The researcher can hereby conclude that due to the strong positive correlation, employee attitude to change as an independent variable does positively impact the adoption of artificial intelligence. Further to that, a multiple regression analysis was run on the constructs, and employee attitude to change was discovered to have a collinearity coefficient that was not significant at a 95% confidence level and was therefore excluded from the model. The researcher can then conclude that while employee attitude to change is strongly positively correlated to artificial intelligence adoption, it is not a significant driver of the phenomenon.

Research Question Four

Does the general population's access to internet impact the adoption of artificial intelligence?

A Pearson correlation test was run to determine the correlation between population access to internet as an independent variable and artificial intelligence adoption as the dependent variable. The results of that Pearson Correlation test indicated the relationship between the population access to internet independent variable and the artificial intelligence adoption dependent variable was significant at a 95% confidence level. The Pearson Correlation coefficient was 0.547, denoting a moderately strong positive relationship between this independent variable and the dependent variable. The researcher can hereby conclude that due to the moderately strong positive correlation, population access to the internet does directly impact the adoption of artificial intelligence. Further to that, a multiple regression analysis was run and population access to internet was found to be a significant predictor of artificial intelligence adoption.

Research Question Five

Does the cost of implementing new digital technologies impact the adoption of artificial intelligence?

A Pearson correlation test was run to determine the correlation between cost of implementation as an independent variable and artificial intelligence adoption as the dependent variable. The results of that Pearson Correlation test indicated that the relationship between the cost of implementation independent variable and the artificial intelligence adoption dependent variable was significant at a 99% confidence level. The Pearson Correlation coefficient was 0.176, denoting a weak positive relationship between this independent variable and the dependent variable. The researcher can hereby conclude that due to the weak positive correlation, cost of implementation as an independent variable does directly impact the adoption of artificial intelligence in a minor way. Further to that, a multiple regression analysis was run on the constructs, and cost of implementation was discovered to have a collinearity coefficient that was not significant at a 95% confidence level and was therefore excluded from the model. The researcher can then conclude that while cost of implantation is slightly positively correlated to artificial intelligence adoption, it is not a significant driver of the phenomenon.

There exists factors that drive the adoption of artificial intelligence in developing markets. The results have revealed that some are stronger than others. The subsequent section will present a discussion of these results.

CHAPTER 6:
DISCUSSION OF RESULTS

6.1 Introduction

The main research objective of this study was to understand the factors that influence the employee readiness to adopt artificial intelligence in frontier markets. The Zambian financial sector was utilised as a proxy for what could be replicated in several industries in frontier and other developing markets. The factors that were revealed through a comprehensive literature review related to clarity in organisational leadership, skill levels of employees, cost of implementing new technologies, employee attitude during moments of organisational change and general access of the population to internet. An electronic survey was sent out to 365 staff members of one of the top four banks in Lusaka, Zambia. The survey centred on discovering the strength of the relationship between the multiple independent variables and the dependent variable artificial intelligence adoption. The sample was selected through non-probability convenience sampling due to the researcher's unique position of being employed by the same bank. A total of 215 staff members accessed the electronic survey, and eventually, 208 staff members completed the survey. A thorough data sanitization exercise reduced the sample size to 185, after which statistical analysis was run on this sample to answer the research questions. The subsequent section will discuss each research question by tying in literature that was previously reviewed.

6.2 Research Question One: Organisational Leadership Clarity

Contemporary literary has pointed to managerial capabilities as significant factors in the adoption and eventual implementation of digital technologies by firms. Alternative theories make reference to the lack of strategic clarity surrounding the implementation of digital technologies which is more of a driving force. The C suite is layered with executives, each with their own area of responsibility, which may sometimes contain significant overlaps. However, it is only in recent times when organisations have realised the importance of having an executive that owns their digital strategy (Bennis, 2013; Curran, 2017).

The usefulness of digital technologies which include cognitive technologies for organisations operating in the fourth industrial revolution is unparalleled due to the dissemination of information. When implemented correctly, smart technologies have the capability of enriching every customer-firm interaction with the gathering of data in order to create unique client profiles which serve to augment the next interaction with the client (Huang & Rust, 2018). The organisation becomes acutely more aware of the environment in which they operate in due to the constant flow of information enabled by the cognitive technologies infused into their processes. The customer of this modern era demands a more personalised service (Edelman & Singer, 2015). The enablement of more efficient client profiling due to more effective feedback with the infusion of technology should translate into far more competent decision making by firms and ultimately improve their competitive edge (Bennis, 2013). Conversely, emerging technologies are not static as they are constantly evolving, it is thus imperative that an organisation not only remains adaptive to these sometimes unexpected changes but closely monitors them in the context of their operating environment (Groen & Walsh, 2013; Joung & Kim, 2017; Rotolo et al., 2015). The emphasis on these measures requires not only strength in leadership but clarity as well in terms of ownership of organisational digital strategies. This becomes more evident when a perusal of organisational annual reports reveal that multiple organisations are placing significant emphasis on digital transformation efforts in their strategic objectives. The mandate for these efforts are no longer abandoned to information technology departments, but recent research shows that chief executive officers are now directly involved in digital technology implementation.

Profit maximisation is still a key metric by which many for profit organisations rate their success. Strategy formulation has usually been centred on profit seeking as the primary objective. Turel and Bart (2014) indicate a shift in the strategy formulation process that looks to embed the organisational digital strategy from inception. Li, Liu, Belitski, Ghobadian and O'Reagan (2016) highlight the need for aligning business strategy development with the development of technological capabilities. These processes need to be spearheaded by the uppermost echelons of leadership if they are to make a meaningful impact.

The collected data coincided with the reviewed literature. Leadership clarity as an independent variable had the highest positive correlation to the dependent variable at 95% confidence level. The Pearson Correlation coefficient of 0.747 proved that leadership clarity had the strongest positive correlation among the independent variables, with the dependent variable, artificial intelligence adoption. Furthermore, after performing a regression analysis on the variables, leadership clarity was found to be a significant predictor of the dependent variable. This ties into arguments derived from literature that organisational leadership can be a significant driver of digital strategy, which would include the adoption of artificial intelligence.

6.3 Research Question Two: Skills Levels Gap

Contemporary literature has been awash with theories of the substitutionary effect on labour that the emergence of automation and other technologies have (Frey & Osborne, 2017). As automation and technology take over, tasks that were previously being done by human labour, will be done by technology. Other theories indicate a more subtle complementary effect that technology will have on labour levels (Autor, 2015). This theory indicates that automation and early forms of technology will replace repetitive, low complexity tasks. This will enable the workforce to upgrade their skill levels and will demand an alteration of job designs but ultimately technology will not displace human labour completely (Arntz et al., 2017). As technology improves, however, and with the emergence of more cognitive technologies such as AI, the debate on their effect on job loss is once again coming to prominence. The researcher, however, believes that once again, the substitutionary effect of these smart technologies have been overstated. Contemporary research has shown limitations in AI's ability to reason, technology has not progressed to a point where human's intuitive nature can be replicated in a computer system (Lee et al., 2017; Marinova et al., 2017; Noor, 2015).

Cognitive technologies have the ability to improve the manner and pace in which a firm has access to information through their ability to process large quantities of data. However, there is a need for personnel entrusted with the interpretation of the processed data to be fully conversant with the technologies and their processes (Ross, 2018). Therefore, the emergence of more cognitive technologies has led to an inevitable alteration of job design as employees up skill themselves in order to increase their skill premiums and be more relevant to the evolving workforce dynamics. The service industry has thus experienced a revival in line with changing workforce dynamics (Buera & Kaboski, 2012). More analytical and intuitive skills are required by employers to complement their investments in smart technologies. However, there is some evidence that the improvement of skills is advancing at a slower pace to the technological change processes. The IT productivity paradox mentioned by Brynjolfsson et al. (2017) refers to organisational delays in developing complementary capabilities in light of rapid technological change and implementation having a delayed effect on organisation productivity.

Technological change is inevitable, however, with it, complementary capabilities of the labour force who use it needs to improve in tandem with its pace of implementation. Decision making in efficient and profitable organisations has shifted from management intuition to data driven analytics. However, an up skilling of data interpretation is required in order for this to be beneficial to organisations. The data collected during this study found that employee skill levels had a significant positive correlation with artificial intelligence adoption. The Pearson Correlation coefficient was 0.717 at a 95% confidence level. This could infer that skill levels of employee is a significant driver of artificial intelligence adoption. However, what the research also discovered is that skill levels and leadership clarity as independent variables were highly positively correlated, with a correlation coefficient of 0.939. This is further evidenced when running a regression analysis, it was discovered that there is a multicollinearity issue with skill levels having the highest collinearity coefficient of 20.62, therefore as a variable it was excluded from the final regression model. Please refer to **Table 5.15**. The skill levels variable's high correlation with leadership clarity could be interpreted using human capital policies. It can be inferred from those statistical findings that leadership is a significant driver of the overall skill levels and skill premiums in organisations. Further research can delve deeper to research this as this was beyond the scope of this study. It can also be inferred that skill levels as an independent variable does have a linear relationship with the dependent variable artificial intelligence adoption. However, the regression analysis findings discovered that it is not a significant predictor of the phenomenon. It can thus be inferred that artificial intelligence adoption by firms can occur regardless of the skill levels of employees to a certain extent. However it is not a significant factor of influence to the employee readiness to adapt to AI.

6.4 Research Question Three: Employee Attitude to Change

Employee readiness for change has been defined in recent research as, "the *employee's feelings, beliefs and intentions about an organisation's strategic change that may provide variations in their routine working practices and procedures, as well as the organizational capability and capacity of its successful implementation*" (Adil, 2016, p.225). The implementation of digital technologies in organisations not only has the ability to augment service delivery to clients but in addition it can alter the work flow and job design of employees. Alterations in job design may at times lead to employee anxiety concerning the change. Recent research has indicated an increase in the workforce opinion regarding the infusion of technologies into their processes, as there is more of alteration to their work process as well as their flow and less of an enhancer of service delivery to customers (Yeo & Marquardt, 2015). The sheer rapid pace of technological change infers that moments of change in organisations that are implementing digital technologies will be quite frequent. While prior research has concentrated on the objective effects of change processes, very little research has sought to understand the individual experiences of employees during times of organisational change in order to better understand it (Rafferty & Jimmieson, 2017).

Rafferty and Jimmieson (2017) indicate that magnitude and frequency of organisational change are significant predictors of employee resistance to change. It follows that the larger the magnitude of the change, the more significant the changes to individual job design and process would be, making the individual employee more wary of the change. Frequent organisational changes would have the same effect. Employees are more wary of change if they feel their relational psychological contract with the organisation has been breached, which can lead to job insecurity. Job insecurity can be viewed through the lens of a breach of relational psychological contract. Relational psychological contracts make reference to workplace situations where an employee will exchange their loyalty and commitment for security and other forms of socio-economic benefits (Shoss, 2017).

The frequency of technological change is expected to increase as technological advances in business persist. Research has shown that in certain instances, employee attitude regarding organisational change can determine just how well that change process will be implemented in the organisation. The collected data during this particular study indicated that there was a significant positive correlation to artificial intelligence adoption. The Pearson Coefficient of correlation of 0.637 indicates a strong positive correlation to artificial intelligence adoption a finding which was consistent with the reviewed literature. However, the post data sanitization and a regression analysis to determine the strength of the link between the variables, the statistical finding was that at a 95% confidence level, employee attitude was not a significant predictor of artificial intelligence adoption. It can be inferred from these findings that technological change is not viewed adversely by the workforce, therefore there is no resistance to its implementation.

6.5 Research Question Four: Population Access to Internet

Developing nations still have prohibitively expensive data costs. The accessibility and affordability of broadband internet is not widespread in developing nations thereby leading to large digital inequalities (Robinson et al., 2015). McKinsey & Company estimate that over two billion people have no access to financial services globally. Approximately one third of the world's population does not have access to financial services (McKinsey & Company, 2016). The majority of these statistics are located in developing nations. It is disquieting that such a significant proportion of the global population are excluded from the formal financial sector. This can be attributed to a host of reasons, among them is access to reliable internet.

Globally, there has been a surge in the use and adoption of technology across every spectrum. The fourth industrial revolution has brought technology usage into prominence and never before has the rate of technological change in the industry been so rapid. Haenssgen (2018) mentions how technological advances can have positive effects on a nation's competitiveness and overall development as long as there is a widespread diffusion of those advances to the majority of that nation's population. Sadly, however, it has been discovered that technological advances are not fully inclusive of the majority of the population in developing nations. The sheer pace of change and magnitude at times has the potential of excluding a large fraction of the population in developing nations, thereby leaving them worse off (Haenssgen, 2018). Haensssgen's 2018 longitudinal case study of the use of mobile phones in the health care system in India concluded that the infusion of mobile phones did increase access to health care in India, but simultaneously it has the potential to create a new form of marginalisation among the poor in India.

There is evidence however, that certain recent technological developments have been successful in developing nations and especially Africa with its highly diverse cultural backdrop. Africa is currently the global leader in mobile money transactions (Chironga et al., 2017). Mobile money transactions can be roughly defined as money transfers outside the formal banking systems. The majority of these mobile money transactions are carried out by mobile network operators and other Fintech's such as Mpesa in East Africa. They are mobile phone based and can be effected from anywhere. In addition to access to reliable internet, cultural diversity can manifest as a significant barrier to technology adoption. An econometric study of ICT diffusion conducted by Grazzi and Vergara (2012) in Paraguay revealed that the heterogeneous nature in which technology is dispersed in areas of high cultural diversity does more to deepen the digital divide than bridge it.

It follows that the population access to reliable internet would be a significant influencing factor of artificial intelligence adoption. An organisation's management would not develop and implement technological solutions that their main client base would have no access to, due to unreliable internet. This is consistent with the findings from the research study. The correlation coefficient for the population access variable in relation to the artificial adoption variable was 0.547. This denotes a fairly moderate positive correlation to the dependent variable and is consistent with factors discussed in literature. A further regression analysis reveals that the population access and leadership clarity variables are the only significant predictors of artificial intelligence adoption. A conclusion can be made that from the conducted statistical analysis, the general population access to reliable internet is a significant factor that an organisation's management strongly consider when adopting and implementing digital technologies.

6.6 Research Question Five: Cost of Implementation

The cost of acquiring and implementing digital technologies is significant. When analysed in comparison with the cost of continuing with manual processes and employing human labour, the cost of acquisition and implementation is substantial and may discourage organisation management to invest. There is a realization especially in developing markets, that due to the under development of supporting infrastructure, the investment into technological advances will be significantly higher than in developed nations (Violino, 2017). However, the question that plagues management is the lack of certainty regarding the time lag between investment and accrual of tangible benefits (Atolagbe, 2017; Novitske, 2018). In addition, is the expense worthwhile if the organisational infrastructure inclusive of its labour component will be unable to deal with additional complexities that are part and parcel of the technological implementations? A popular opinion is that it will be a long while until artificial intelligence will be a threat to human capital in Africa, but rather human labour will continue playing a complementary role to technology (Sillah, 2015).

An additional factor to consider is the tenure of office of most Chief Executive Officers (CEOs) in organisations that offer financial services. It is common place for CEO mandates to range from three to five years. CEO's by nature are answerable to their shareholders and during their tenure, they are tasked with profit maximisation and cost optimization. Technological changes will affect employment levels by re-defining the skills mix of potential employees (Castro Silva & Lima, 2017). Furthermore, there exists research that shows us that advances in technology are skill biased in the sense that low complexity jobs can and are being replaced and it will lead to increased demand for better skilled employees (Ugur et al., 2018). In an African context, human labour will not be displaced in the near future by technology. Therefore, any investments in technology will be an additional cost to company with the labour costs. With short tenures of office, most CEO's may not be keen to make significant investments in technology, as they run the risk of worsening their cost to income ratio and will not see the return on their investment before they leave ultimately.

The collected data on this variable was the most surprising of all. The researcher initially was of the opinion after a comprehensive literature review that cost would be a significant factor in the adoption of artificial intelligence. However, of all the independent variables, it had the lowest correlation to the dependent variable. The Pearson Correlation coefficient was 0.176, which denotes a weak positive correlation to the dependent variable. A regression analysis was then run and further evidence of its lack of significance as a factor was discovered when formulating the final regression model. The initial regression model had a multicollinearity concern with the skill levels and leadership variable displaying a high level of correlation. The skills level variable was then excluded from the model in order to improve the model. However, this also proved that both employee attitude and cost had no statistical significance to the model and also had to be excluded. We can then infer that cost is not a factor that management consider when adopting digital technologies, and does not have an impact on the readiness of employees to adapt to AI and other digital technologies.

6.7 Summary of Discussion

It must be noted that the data collected from the workforce in one bank may not be completely representative of the entire financial sector. The bank was chosen to represent the Zambian financial sector due to its size and relevance in the market it operates in. However, it must be noted that organisational behaviour may differ from bank to bank depending on the dynamics in which they operate. For the purposes of this study, the bank utilised as the sample is representative of the Zambian financial sector.

The research study aimed to understand the factors that drive employee readiness to adopt artificial intelligence in a frontier markets context. The Zambian financial sector was utilised as a case study for the research. The findings revealed that organisational leadership clarity and the Zambian population's access to reliable and affordable internet were the two most significant drivers of artificial intelligence adoption in the Zambian financial sectors. The other factors investigated were namely employee skill levels, cost of implementation and employee attitude to change. The findings suggest that although these factors do play a minor role in determining artificial intelligence adoption, they have very little significance in the overall management decision and in the readiness of employee to adapt to AI.

CHAPTER 7:
CONCLUSION

7.1 Introduction

The purpose of this research study was to understand the factors that influence the readiness of banking industry employee to adopt artificial intelligence in frontier markets. To that end, the study utilised one of the major banks in Zambia as a sample to represent the Zambian financial sector. The previous chapter discussed the findings of the research in terms of the research objectives and literature that was reviewed during the study. The following section will discuss each of these findings as a way of offering recommendations to organisations. The academic implications of the study will then follow. Finally, the chapter will be concluded with a section on the limitations incurred during the study and based on these limitations, areas for further research will be suggested.

7.2 Principal Findings

The data collected revealed five principal findings which are outlined below;

1. Clarity in organisational leadership is a significant predictor of artificial intelligence adoption in the Zambian financial sector;
2. Employee skill levels are not a significant predictor of artificial intelligence adoption in the Zambian financial sector;
3. Employee attitude to change is not a significant predictor of artificial intelligence adoption in the Zambian financial sector;
4. General access to reliable internet is a significant predictor of artificial intelligence adoption in the Zambian financial sector;
5. Cost of implementation is not a significant predictor of artificial intelligence adoption in the Zambian financial sector.

The subsequent section will now discuss these findings in more depth.

7.2.1 Leadership Clarity

The leadership clarity independent variable had the highest correlation with the dependent variable, artificial intelligence adoption. Subsequent to a rigorous regression analysis where a few other independent variables were excluded from the final regression model, the findings discovered that leadership clarity was a significant predictor of artificial intelligence adoption. The strong positive correlation between leadership clarity and artificial intelligence adoption is consistent with research conducted by Bennis (2013), Shao, Feng and Hu (2016) as well as Alos-Simo et al. (2017) who support the need for senior management focus on the implementation of technological change initiatives. A common criticism of technological change initiatives is the seemingly lack of ownership of the digital strategy by senior executives. The lack of senior executives tasked with solely the execution of the digital strategy of organisations can lead to a lack of focus regarding the implementation of these strategies. Technological initiatives need to be driven by the organisation’s most senior executives in order for these initiatives to have traction (Alos-Simo et al., 2017; Lu, 2015).

A digital strategy should be part of an organisation’s strategic objectives. The majority of Zambian banks have some form of digital transformation in their strategy documents (Barclays Zambia, 2018; FNB Zambia, 2018; Stanbic Bank Zambia, 2017). What seems to lack, however, is deliberate efforts to have a senior executive solely in charge of the execution of digital strategy. The researcher is not aware of any Zambian bank that has a chief digital officer, who is part of the senior executive committee. Therefore, there is a digital strategy, but no one to own it. Furthermore, the siloed nature of the banking sector means, every business unit will have their own digital strategy as well as initiatives and there will be a lack of alignment concerning digital strategy in the organisation. As the findings have shown, for artificial intelligence adoption to occur, and for sufficient employee readiness to adapt, there requires organisation clarity concerning leadership.

7.2.2 Employee Skill Level

Employee skill levels as an independent variable equally had a strong positive correlation with the dependent variable, artificial intelligence adoption. This is consistent with research done by Berger and Frey (2016), whose findings from their *OECD Social, Employment and Migration Working Paper No. 193* suggested that even though the rapid emergence of technology has compelled the need for employees to up skill themselves, the pace of skills improvement is trailing that of recent technological change. Cognitive technologies have created a shift from management decision making being based more on intuition to more data analytics driven decision making. What has trailed, however, is the building of complementary capabilities in human labour in order to accurately interpret the data analysed. Recent research has indicated evidence of flawed decision making when interpreting data from Management Information Systems (MIS) due to a perceived deficiency in skill levels (Lyytinen & Grover, 2017).

The pertinent question to ask, however, is if employee skill level is a significant factor in the adoption of artificial intelligence by firms. There is a strong positive correlation between employee skill levels and artificial intelligence adoption. However, when conducting the regression analysis, the researcher discovered a multicollinearity issue with the employee skill level as an independent variable of the dependent variable, artificial intelligence. It would be safe for the researcher to infer that employee skill level is not a significant factor of artificial intelligence adoption. The research findings conclude that the qualifications and skill levels of employees are not a significant factor when business is looking to implement digital technologies like artificial intelligence. The research additionally revealed that the participants of the study were relatively highly qualified. The data collected revealed that 81.73% of the participants had undergraduate and/or post graduate qualifications. The exact split being that 44.71% had undergraduate degrees, while the remaining 37.02% had post graduate qualifications. This is indicative of a highly skilled workforce. This was contrary to the researcher’s initial assumptions that most organisations in frontier markets delay the adoption of AI due to the lack of sufficient skills in their workforce.

7.2.3 Employee Attitude to Change

The employee attitude to change variable was found to have a strong positive correlation to the dependent variable, artificial intelligence. However, after a series of data sanitization exercises, during the regression analysis, the researcher discovered that as an independent variable, employee attitude to change was not a significant predictor of artificial intelligence adoption. This is inconsistent with studies done by Rafferty and Jimmieson (2017) who hypothesised that the magnitude and frequency of change had a strong positive correlation with employee resistance to change. Their theory followed that the bigger the magnitude of change, the more affected the individual job designs would be and thus, the higher the level of employee anxiety. Furthermore, the more frequent the change is, the more anxious employees can get and the more resistant they are to the change initiative. Further to that, additional research has indicated that employees with relational contract values, who do not feel like their psychological contracts are being breached, will exercise more enthusiasm to the change initiative as their job security is not threatened (Guo et al., 2017).

The frequency of technological change initiatives is bound to be frequent and the researcher's initial assumptions upon reviewing literature on the subject indicated that employee attitude to change would be a significant predictor of artificial intelligence adoption. The findings of this particular research study conclude that this is not actually the case. The employee attitude to change variable is positively correlated to artificial intelligence adoption but the findings state that it is not a significant predictor of the phenomenon. The data revealed that employees seemed relatively open to disruptions caused by technological change.

7.2.4 Population Access to Technology

The independent variable population access to technology has a moderate positive correlation to the dependent variable, artificial intelligence adoption. Furthermore, the researcher discovered when running the regression analysis that, in addition to leadership clarity, population access to technology was a significant predictor of artificial intelligence. This is consistent with findings from Haenssgen (2018) who concludes that the benefits on development and competitiveness that technological advances can bring about to a nation may not be fully inclusive of the majority of the population to the digital inequalities that exist in developing nations. The prohibitive costs of reliable broadband internet ensure that the digital inequalities that exist in developing do not get addressed (Robinson et al., 2015).

Business thus needs to be cognisant of the challenges they face when adopting digital technologies. They need to ensure that the digital solutions they offer their client base will be applicable to existing clients and potential ones in terms of platform suitability. Alternatively, they will need to engage regulators to ensure that broadband internet costs are affordable for the majority of the population if they are increasing their presence into the non-banked segments of the population.

7.2.5 Cost of Implementation

Cost of implementation as an independent variable was found to have a weak positive correlation to the dependent variable, artificial intelligence. A regression analysis further revealed that it was not a significant predictor of artificial intelligence adoption. Recent news reports have indicated that due to the under developed nature of IT infrastructure in Africa, significant capital investments would be required in technology in order for Africa to compete with the developed world (Violino, 2017). To add to that complexity, there is a considerable time lag between the capital investment and the reaping of any tangible benefits (Novitske, 2018). Business CEO's currently have shorter tenures at the helm of organisations. Coupled with a misalignment of their top deliverables which usually centre on profit maximisation and cost optimization, CEO's may not be motivated to commit substantial investments into technological advances for their organisation.

The research findings, however, debunk that theory by stating that the cost is not a significant factor of artificial intelligence adoption. It can be inferred that business will invest in the most appropriate digital technologies irrespective of the cost, and employee sentiment is that they will be able to adapt to it.

7.3 Implications for Business

Frontier markets are considered underexplored areas of great potential. Selected frontier markets in the African continent can offer significant positive returns on investment due to their potential to exhibit heightened economic growth. Africa has seen several organisations seeking to set up shop in order exploit the substantial returns. Technological infusions into business operations have since taken precedence in order to achieve competitive superiority amongst rival firms. These rapid changes have been imposed on the workforce in frontier markets. The findings of this study are relevant to understand the implications of the adaptability of the workforce in adopting this precipitated technological change.

The research study findings concluded that the bank in question was marginally familiar with the factors that influence the adoption of artificial intelligence in the banking sector in frontier markets. Contrary to the researcher's assumptions prior to undertaking this research, the most significant drivers of artificial intelligence adoption are clarity in organisational leadership and the population's access to reliable internet. Leadership is a construct that can be influenced internally, while access to the internet is out of the organisation's scope of influence. Therefore, in order for business to be able to diffuse digital technologies throughout the organisation, the construct of leadership will need to be addressed.

Most financial services organisations place a strategic emphasis on digital transformation initiatives, however, this is not followed by executive ownership of the initiatives. In order for the initiatives to be more impactful, organisation structure will need to be altered to reflect this focus on digital transformation. Senior executives will not only need to drive these initiatives but will also require to own them. A recommendation which has already been alluded to in previous sections is the need for an organisation to appoint a senior executive whose sole responsibility is the formulation and execution of digital strategy.

7.4 Limitations of Study

The research study employed a non-probability, convenience method of sampling to select the respondents to the study. This could have created a bias and may not have been representative of the population as a whole. The use of this sampling method was intended to optimally pick the most suitable respondents to the study and by effect may have been unrepresentative of the target population.

Secondly, an additional limitation of this study is that, the scope of the research was intended to be representative of the Zambian financial sector, however, data was collected from one of the banks, using quantitative methods. In order to fully exhaust the comprehensive list of factors that contribute to artificial intelligence adoption, the researcher believes a qualitative study would have uncovered more valuable insights. In order to appear more representative of the target population, qualitative interviews with decision makers of banks representing different dynamics would have revealed valuable insight. Zambia currently has 19 registered commercial banks. An alternative research path would have been to use the workforce of four of these banks as the representative sample, the banks could have been chosen using the following criteria; one international bank, one small local bank, one big local bank and finally one bank that offers specialised offerings. This would have ensured that the sample was more representative of the target population, due to these facts, dynamics between the banks could differ because of the circumstances in which they operate in.

Thirdly, an additional limitation is that the scope of the study was limited to the financial sector. The formulated model was essentially supposed to be replicated in other industries. However, dynamics are very different from sector to sector. For example, the manufacturing industry will have diversely different dynamics to the financial sector. One such difference is that in manufacturing, task automation is more prevalent than in the financial sector, and job losses due to task automation are frequent. Therefore, the findings revealed from that industry would differ greatly from the findings of this study.

Fourth and finally, the role of regulation in the adoption of artificial intelligence adoption was not explored in this particular study. Banking is one of the most regulated industries, however, the researcher could not find any academic literature or theory that explored the extent to which regulation could be a barrier or an accelerator of employee readiness to artificial intelligence adoption. Therefore, regulation as a subset of the influencing factors was excluded from this deductive study.

7.5 Suggestions for Future Research

Below is a summary of certain areas that could benefit from future research based on the limitations of this particular study. One particular area that could benefit from further research would be to investigate the impact of artificial intelligence adoption on the employee engagement levels. Literature is abound with theories of employee anxiety during periods of job insecurity caused by poorly communicated and implemented change initiatives in organisations. Artificial intelligence is a relatively trending topic at the moment and its adoption in industries may create technological anxiety among the workforce. A suggestion for future research would be to investigate the impact of artificial intelligence adoption on the engagement levels of employees.

An additional area of further research would be to triangulate the aspects of leadership outside of leadership clarity that acts as a moderator or inhibitor of artificial intelligence adoption in organisations. The scope of this researcher focused solely on clarity in organisation leadership. The findings determined that leadership clarity is the most significant predictor of artificial intelligence adoption. It would be interesting if further research was undertaken to determine what aspects of leadership are the most significant predictors of artificial intelligence adoption.

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APPENDICES

9.1 Appendix A: Survey

Gordon Institute of Business Science
University of Pretoria

Understanding the factors that influence the adoption of artificial intelligence in emerging markets

Dear Participant,

I am undertaking my Masters in Business Administration degree with the Gordon Institute of Business Science, an affiliate of the University of Pretoria in South Africa.

I am currently conducting research to understand the factors that influence the adoption of artificial intelligent (AI) in emerging markets and any subsequent effect they may have on a workforce. My research will utilise the Zambian financial sector as a case study.

Consequently, you are requested to please participate in the following short questionnaire. The questionnaire should not take you longer than 10 minutes to complete. Kindly do note that participation in this survey is completely voluntary, and you can withdraw at any given time without penalty.

Furthermore, please do take note that your participation will be completely anonymous as all data collected and reported will be aggregated to represent the group total. By completing this survey, you are hereby indicating that you have voluntarily participated in the research. For any further clarifications of any concerns you may have, please do not hesitate to contact either myself or my supervisor on the contact details provided below;

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Gordon Institute of Business Science
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Understanding the factors that influence the adoption of artificial intelligence in emerging markets

Personal Information

Please tell us a little about yourself. Kindly take note that all responses are anonymous, and only aggregated information will be reported.

* 1. Please specify your age

- 20 – 29
- 30 – 39
- 40 – 49
- 50 – 59
- 60 +

* 2. Please specify your gender

- Male
- Female

* 3. Please specify your nationality (Zambian, Other)

- Zambian
- Other (Specify)

Other (please specify)

* 4. Please specify the length of service (years) at your current place of employment

- 0 – 2
- 3 – 5
- 6 – 10
- 11 – 15
- 16+

5. Please specify your current job grade

- Clerical
- Unionsed
- Lower Management
- Middle Management
- Senior Management
- Executive

* 6. Please specify your current employment status with your organisation

- ◯ Temporary Contract
- ◯ Expatriate
- ◯ Permanent Contract

* 7. Please specify your highest educational level attained

- ◯ Did not complete secondary school
- ◯ Tertiary diploma
- ◯ Secondary school
- ◯ Undergraduate degree
- ◯ Post-secondary school certificate
- ◯ Postgraduate qualification

Gordon Institute of Business Science
University of Pretoria

Understanding the factors that influence the adoption of artificial intelligence in emerging markets

Artificial Intelligence Readiness

The next few questions are aimed to gauge the current state of the organisation in terms of Artificial Intelligence (AI) readiness and capabilities. Artificial intelligence is a term first coined in 1956 by John McCarthy. It is currently still a developing field and thus does not have an accepted theory. However for purposes of this study, AI has been referred to by numerous thought leaders as a branch of computer science that deals with the capability of machines, and computers to simulate intelligent and cognitive human behaviour.

The first four questions can be answered by picking the answer which resonates most with you, please indicate to what extent you agree or disagree with the statements posed. The fifth question is based on your opinion on the state of organisation, and will just require you to answer affirmatively or negatively.

8. Artificial intelligence as a concept is something I am fairly comfortable with

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

9. The organisation uses a variety of sophisticated systems, and software across the network

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

10. The organisation has a dedicated IT department with a variety of IT specialists who interact with all levels of the organisation regularly

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

4

11. The organisation provides sophisticated software that makes the analytical part of my job easier

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

* 12. In your opinion, is the organisation proactive in keeping up to date with technological developments in the sector/industry?

- Yes
- No

Gordon Institute of Business Science
University of Pretoria

Understanding the factors that influence the adoption of artificial intelligence in emerging markets

Employee attitude to change

The following questions are designed to gauge the extent to which employee attitude is an influential factor in the adoption of certain initiatives. Please indicate to what extent you agree or disagree with the statements posed.

13. I have a positive attitude towards change in the organisation, and I always look forward to trying new things

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

14. The organisation is proactive in communicating any changes before the change is implemented

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

15. Inadequately communicated adjustments in my job design make me anxious

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

16. Technology will eventually replace my role in the workplace

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

6

Skill levels

The following questions are designed to gauge the extent to which employee skill levels play a role in the adoption rate of certain projects. Please indicate to what extent you agree or disagree with the statements posed.

17. I have the adequate skills for my current role at work

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

18. The organisation provides adequate training on new systems and products before they are launched

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

19. I am comfortable with the use of technology to help me do my job better

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

20. I use electronic platforms extensively and comfortably in my current role

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

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Understanding the factors that influence the adoption of artificial intelligence in emerging markets

Clarity in leadership

The following questions are designed to gauge to what extent organisation leadership can play a role in the adoption of digital technologies. Please indicate to what extent you agree or disagree with the statements posed

21. The organisation has a well defined digital strategy

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

22. The organisation in terms of personnel and resources places considerable emphasis on the implementation of its digital strategy

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

23. The organisation is proactive in communicating any developments concerning digital or technological advances in the organisation

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

9

24. The organisation's leadership is effective at communicating the future benefits of implementing its digital strategy

- Strongly agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

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Understanding the factors that influence the adoption of artificial intelligence in emerging markets

Population access to technology

The following questions aim to gauge how much of a role the general population's access to internet and usage of electronic platforms plays in the organisation's adoption of certain digital technologies. Please indicate to what extent you agree or disagree with the statements posed.

25. Most of the organisation's clients have a good understanding of the bank's technology

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

26. Most of the organisation's client's embrace all new technological products and services with ease

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

27. Most of the organisation's electronic platforms are extensively used by the bank's clients

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

11

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Understanding the factors that influence the adoption of artificial intelligence in emerging markets

Cost of implementation

The following questions are designed to gauge to what extent cost may be a factor in the adoption of new digital technologies. Please indicate to what extent you agree with the statements posed.

28. New technology is necessary to keep the organisation competitive

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

29. The organisation should upgrade their technology regularly, regardless of the cost

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

30. The cost of new technologies is insignificant compared to the benefits it may bring

- Strongly Agree
- Agree
- Somewhat Agree
- Undecided
- Somewhat Disagree
- Disagree
- Strongly Disagree

9.2 Appendix B: Bank Approval to Conduct Research

7th August, 2018

The Chairperson

Ethical Clearance Committee

The Gordon Institute of Business Science

PO Box 787602

26 Melville Road

Ilovo, Sandton

South Africa

Dear Sir/Madam

PERMISSION TO COLLECT DATA FROM STANBIC BANK

This letter serves to confirm that Stanbic Bank Zambia has granted permission to Akayombokwa Mutumba to collect data from Stanbic Bank employees as part of his research dissertation.

The topic he will be exploring is "Understanding the factors that influence the adoption of artificial intelligence in emerging markets," using the Zambian financial sector as a case study to formulate a model that explores the barriers of A.I. adoption in developing markets. The study will be quantitative in nature and will be administered through the use of an online survey.

We hope the approval given will suffice to enable Akayombokwa complete his research dissertation.

Yours faithfully,

Enock Kabwe

Acting Head Human Capital

Head Office, Stanbic House, Plot 2375, Addis Ababa Drive, P O Box 31955, Lusaka
Tel: +260 211 370000 - 18; www.stanbicbank.co.zm

Stanbic Bank Zambia Limited. Registered Commercial Bank – Registered in Zambia Reg. No. 6559
A Member of Standard Bank Group
Directors: Dr. Austin A.K. Mwape (Chairperson), Leina L Gabaraane (Chief Executive), Greg. R. Brackenridge (Regional Chief Executive), Helen Lubamba (Head of Corporate and Investment Banking) Wabei Mangambwa, Luke C. Mbewe, Don R. Stacey, Emmanuel B Mutati, Mwenzi M. Mulenga , Milangu N Kampata, Bejoy J Nettikadan,

Company Secretary: Doris C. Tembwe

Stanbic Bank Moving Forward™

9.3 Appendix C: Ethical Clearance Approval

Gordon Institute of Business Science
University of Pretoria

17 August 2018

Mutumba Akayombokwa

Dear Akayombokwa

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

Please note that approval is granted based on the methodology and research instruments provided in the application. If there is any deviation change or addition to the research method or tools, a supplementary application for approval must be obtained

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee

Gordon Institute of Business Science

University of Pretoria

9.4 Appendix D: Tests For Linearity

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Cost	185	5.02	0.74	5.76	2.02	0.08	1.11	1.23	1.02	0.18	0.45	0.36
Leadership	185	5.77	1.03	6.80	2.50	0.07	0.93	0.86	1.22	0.18	2.58	0.36
SkillsGap	185	5.33	1.13	6.46	2.57	0.07	0.89	0.78	1.13	0.18	2.15	0.36
PopAccess	185	4.83	1.09	5.92	3.13	0.08	1.08	1.16	0.57	0.18	- 0.48	0.36
EmpAtt	185	5.74	1.12	6.86	2.76	0.09	1.16	1.34	1.05	0.18	0.79	0.36
AI	185	4.65	1.12	5.77	2.62	0.07	0.91	0.83	0.69	0.18	0.08	0.36
Valid N (listwise)	185											

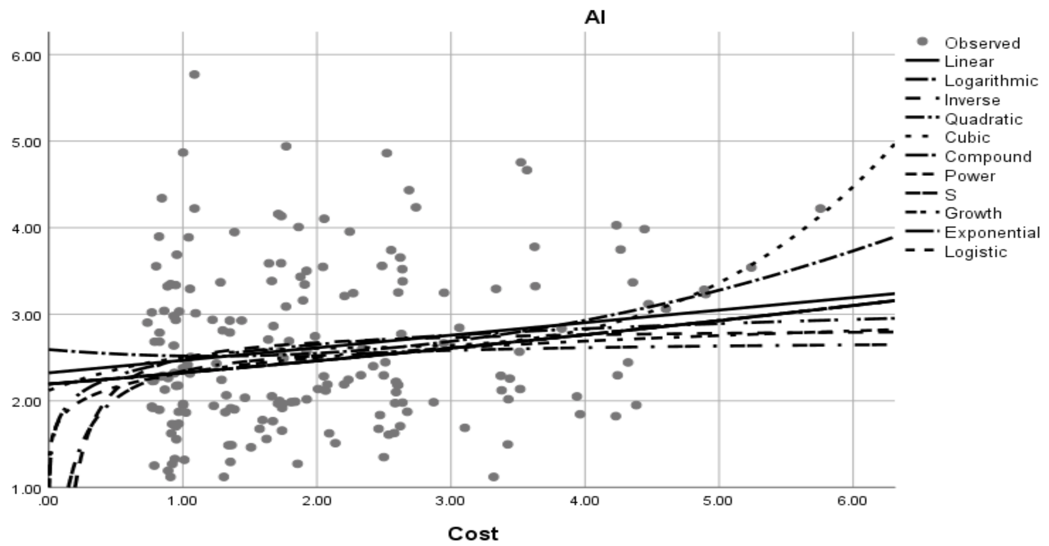
Frequencies

		Cost	Leadership	SkillsGap	PopAccess	EmpAtt	AI
N	Valid	185	185	185	185	185	185
	Missing	0	0	0	0	0	0
Mean		2.0159	2.5005	2.5703	3.1300	2.7634	2.6154
Median		1.7452	2.2879	2.4310	2.8172	2.4134	2.3784
Mode		.74[a]	1.03[a]	1.13[a]	1.09[a]	1.12[a]	1.12[a]
Skewness		1.016	1.219	1.134	0.572	1.052	0.694
Std. Error of		0.179	0.179	0.179	0.179	0.179	0.179
Kurtosis		0.446	2.577	2.153	-0.476	0.786	0.076
Std. Error of Kurtosis		0.355	0.355	0.355	0.355	0.355	0.355
Sum		372.94	462.58	475.51	579.06	511.24	483.85

a. Multiple modes exist. The smallest value is shown

Curve Fit : Independent Variable : Cost of Implementation

Model Summary and Parameter Estimates									
Dependent Variable:	AI								
	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.031	5.863	1	183	0.016	2.323	0.145		
Logarithmic	0.024	4.452	1	183	0.036	2.468	0.263		
Inverse	0.017	3.172	1	183	0.077	2.852	-0.362		
Quadratic	0.038	3.596	2	182	0.029	2.592	-0.127	0.053	
Cubic	0.043	2.743	3	181	0.045	2.120	0.593	-0.246	0.035
Compound	0.034	6.401	1	183	0.012	2.194	1.059		
Power	0.026	4.954	1	183	0.027	2.323	0.106		
S	0.019	3.538	1	183	0.062	0.997	-0.146		
Growth	0.034	6.401	1	183	0.012	0.786	0.058		
Exponential	0.034	6.401	1	183	0.012	2.194	0.058		
Logistic	0.034	6.401	1	183	0.012	0.456	0.944		
The independent variable is Cost.									



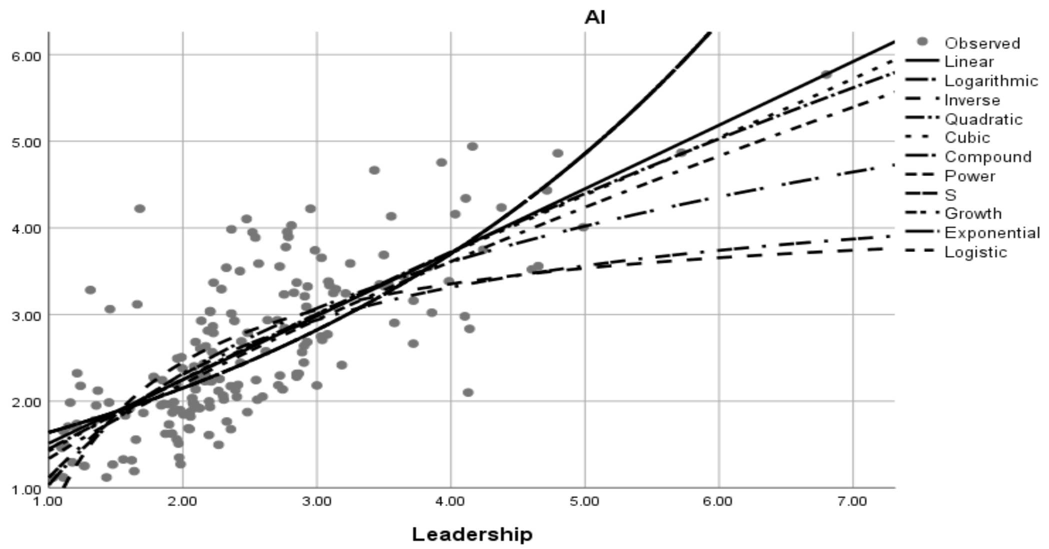
Curve Fit : Independent Variable : Leadership Clarity

Model Summary and Parameter Estimates

Dependent Variable: AI

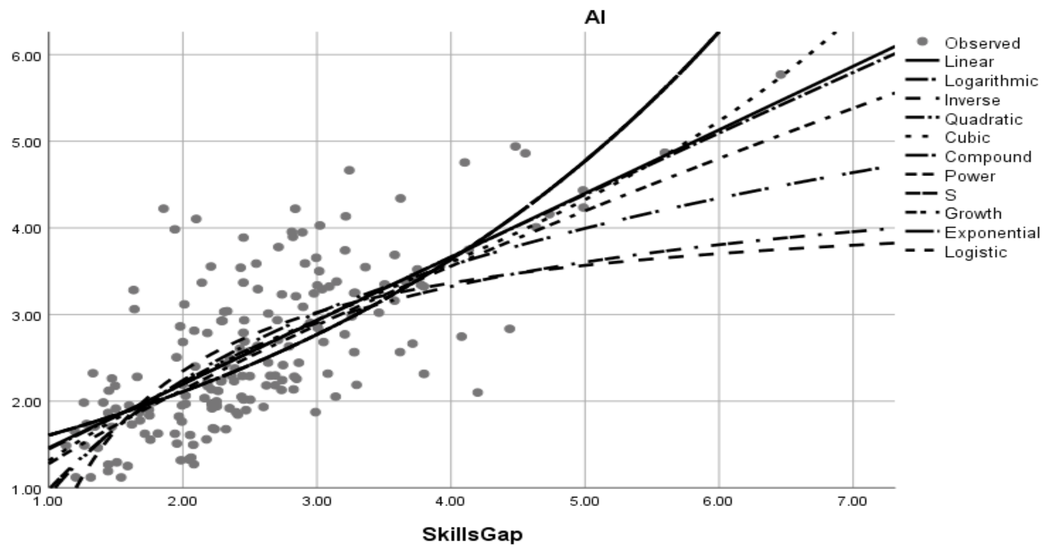
Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.559	231.521	1	183	0.000	0.779	0.735		
Logarithmic	0.532	207.682	1	183	0.000	1.032	1.857		
Inverse	0.443	145.599	1	183	0.000	4.258	-3.616		
Quadratic	0.560	115.682	2	182	0.000	0.606	0.863	-0.021	
Cubic	0.560	76.737	3	181	0.000	0.495	0.987	-0.061	0.004
Compound	0.524	201.804	1	183	0.000	1.250	1.312		
Power	0.544	218.111	1	183	0.000	1.337	0.717		
S	0.490	175.861	1	183	0.000	1.561	-1.451		
Growth	0.524	201.804	1	183	0.000	0.223	0.272		
Exponential	0.524	201.804	1	183	0.000	1.250	0.272		
Logistic	0.524	201.804	1	183	0.000	0.800	0.762		

The independent variable is Leadership.



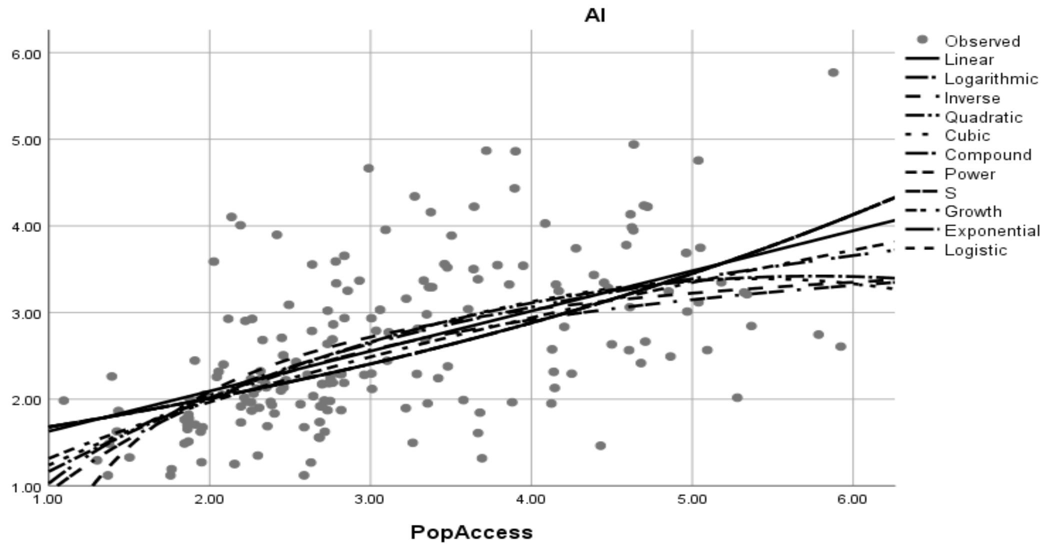
Curve Fit : Independent Variable : Employee Skill Levels

Model Summary and Parameter Estimates									
Dependent Variable:	AI								
	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.507	188.539	1	183	0.000	0.729	0.734		
Logarithmic	0.485	172.634	1	183	0.000	0.914	1.914		
Inverse	0.423	134.134	1	183	0.000	4.381	-4.068		
Quadratic	0.508	93.773	2	182	0.000	0.688	0.764	-0.005	
Cubic	0.510	62.677	3	181	0.000	0.107	1.397	-0.212	0.020
Compound	0.479	168.507	1	183	0.000	1.224	1.313		
Power	0.497	180.683	1	183	0.000	1.278	0.739		
S	0.464	158.430	1	183	0.000	1.608	-1.626		
Growth	0.479	168.507	1	183	0.000	0.203	0.272		
Exponential	0.479	168.507	1	183	0.000	1.224	0.272		
Logistic	0.479	168.507	1	183	0.000	0.817	0.762		
The independent variable is SkillsGap.									



Curve Fit : Independent Variable : Population Access to Technology

Model Summary and Parameter Estimates									
Dependent Variable:	AI								
	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.299	78.222	1	183	0.000	1.166	0.463		
Logarithmic	0.314	83.736	1	183	0.000	1.027	1.468		
Inverse	0.294	76.245	1	183	0.000	3.982	-3.795		
Quadratic	0.318	42.478	2	182	0.000	0.118	1.145	-0.099	
Cubic	0.318	28.197	3	181	0.000	0.397	0.861	-0.010	-0.009
Compound	0.311	82.530	1	183	0.000	1.403	1.197		
Power	0.337	93.054	1	183	0.000	1.315	0.581		
S	0.328	89.283	1	183	0.000	1.453	-1.529		
Growth	0.311	82.530	1	183	0.000	0.339	0.180		
Exponential	0.311	82.530	1	183	0.000	1.403	0.180		
Logistic	0.311	82.530	1	183	0.000	0.713	0.835		
The independent variable is PopAccess.									



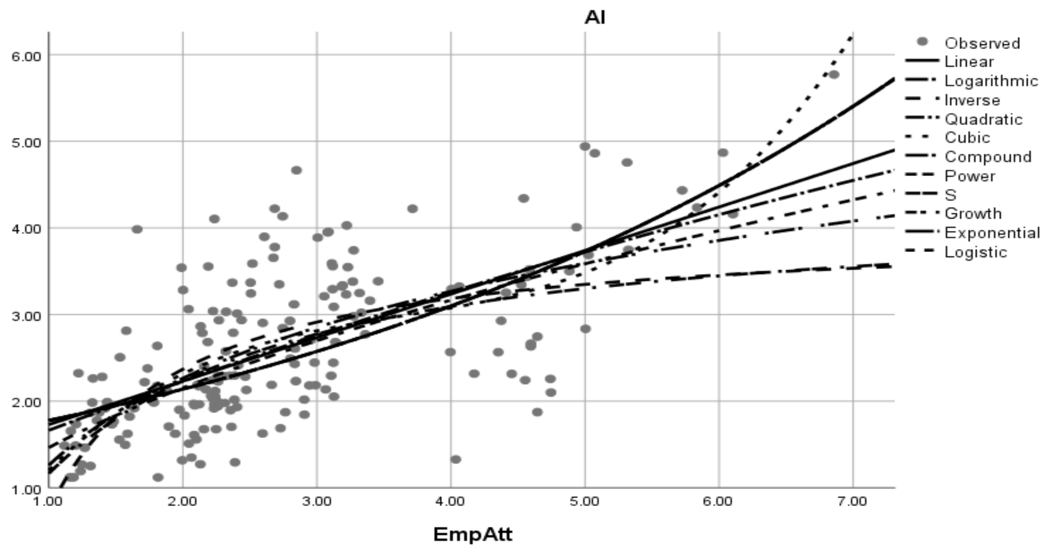
Curve Fit : Independent Variable : Employee Attitude to Change

Model Summary and Parameter Estimates

Dependent Variable: AI

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.406	125.271	1	183	0.000	1.227	0.502		
Logarithmic	0.407	125.702	1	183	0.000	1.260	1.449		
Inverse	0.369	107.236	1	183	0.000	4.000	-3.263		
Quadratic	0.407	62.554	2	182	0.000	1.065	0.616	-0.017	
Cubic	0.446	48.665	3	181	0.000	-0.903	2.727	-0.685	0.063
Compound	0.380	112.188	1	183	0.000	1.477	1.204		
Power	0.413	128.708	1	183	0.000	1.464	0.557		
S	0.403	123.769	1	183	0.000	1.454	-1.301		
Growth	0.380	112.188	1	183	0.000	0.390	0.185		
Exponential	0.380	112.188	1	183	0.000	1.477	0.185		
Logistic	0.380	112.188	1	183	0.000	0.677	0.831		

The independent variable is EmpAtt.



9.5 Appendix E: Measurement Model

AMOS Measurement Model Summary

		MM0	MM1	MM1	MM2	MM3	MM4	MM5	MM final
		start	mod ind 20	mod ind 4	rem COST1	rem AI1	rem EMAT1	rem SKG1 AI2	
CMIN/DF	<3.00	1.679	1.490	1.417	1.396	1.462	1.507	1.463	1.463
RMR	<0.09	0.083	0.081	0.079	0.082	0.082	0.085	0.089	0.089
GFI	>0.95	0.880	0.895	0.901	0.908	0.910	0.914	0.931	0.931
AGFI	>0.80	0.842	0.861	0.867	0.874	0.874	0.876	0.892	0.892
TLI	>0.95	0.899	0.927	0.938	0.945	0.942	0.942	0.956	0.956
CFI	>0.95	0.915	0.939	0.948	0.955	0.954	0.955	0.968	0.968
RMSEA	<0.05	0.061	0.052	0.048	0.046	0.050	0.053	0.050	0.050
PCLOSE	>0.05	0.084	0.411	0.596	0.637	0.481	0.387	0.475	0.475
HOELTER 0.05	>150	131	148	155	159	154	151	161	161

AMOS Final Measurement Model

		MM final	SM	SM	SM
				imp 1	imp 2
CMIN/DF	<3.00	1.463	1.629	1.479	1.399
RMR	<0.09	0.089	0.090	0.090	0.082
GFI	>0.95	0.931	0.867	0.883	0.889
AGFI	>0.80	0.892	0.825	0.844	0.850
TLI	>0.95	0.956	0.880	0.909	0.924
CFI	>0.95	0.968	0.901	0.926	0.939
RMSEA	<0.05	0.050	0.058	0.051	0.047
PCLOSE	>0.05	0.475	0.108	0.434	0.664
HOELTER 0.05	>150	161	132	146	154

Regression Weights

Regression Weights: (Group number 1 - Default model)							
			Estimate	S.E.	C.R.	P	Label
LEAD_1	<---	Leadership	0.703	0.07	10.079	***	par_1
LEAD_3	<---	Leadership	0.965	0.072	13.379	***	par_2
LEAD_4	<---	Leadership	1				
LEAD_2	<---	Leadership	0.792	0.072	11.058	***	par_3
SK_G_2	<---	Leadership	0.853	0.09	9.482	***	par_4
EM_AT_2	<---	Leadership	0.919	0.108	8.524	***	par_5
SK_G_3	<---	skills_gap	0.903	0.207	4.37	***	par_6
SK_G_4	<---	skills_gap	1				
POP_AT_2	<---	Pop_access	1				
POP_AT_1	<---	Pop_access	0.962	0.086	11.244	***	par_7
POP_AT_3	<---	Pop_access	0.797	0.092	8.698	***	par_8
COST_3	<---	Cost	0.742	0.214	3.459	***	par_9
COST_2	<---	Cost	1				
AI_4	<---	Artificial_Intel	1				
AI_5	<---	Artificial_Intel	0.273	0.055	4.981	***	par_10

Correlations

Correlations: (Group number 1 - Default mode			
			Estimate
Leadership	<-->	skills_gap	0.408
Leadership	<-->	Pop_access	0.468
Leadership	<-->	Cost	0.08
Leadership	<-->	Artificial_Intel	0.584
skills_gap	<-->	Pop_access	0.255
skills_gap	<-->	Cost	0.247
skills_gap	<-->	Artificial_Intel	0.326
Pop_access	<-->	Cost	0.238
Pop_access	<-->	Artificial_Intel	0.462
Cost	<-->	Artificial_Intel	0.244
e1	<-->	e4	0.413
e5	<-->	e6	0.239
e4	<-->	e6	-0.147

Variances

Variances: (Group number 1 - Default model)							
			Estimate	S.E.	C.R.	P	Label
Leadership			0.956	0.136	7.002	***	par_24
skills_gap			0.278	0.078	3.544	***	par_25
Pop_access			1.364	0.217	6.295	***	par_26
Cost			1.752	0.515	3.401	***	par_27
Artificial_Intel			1.142	0.293	3.905	***	par_28
e1			0.552	0.065	8.495	***	par_29
e2			0.387	0.058	6.719	***	par_30
e3			0.332	0.055	6.068	***	par_31
e4			0.529	0.066	8.069	***	par_32
e5			0.908	0.106	8.591	***	par_33
e6			1.355	0.155	8.732	***	par_34
e7			0.127	0.051	2.5	0.012	par_35
e9			0.279	0.067	4.175	***	par_36
e13			0.613	0.112	5.453	***	par_37
e14			0.591	0.105	5.607	***	par_38
e15			1.055	0.135	7.828	***	par_39
e16			1.371	0.302	4.548	***	par_40
e17			-0.017	0.482	-0.035	0.972	par_41
e18			1.057	0.239	4.414	***	par_42
e20			0.138	0.021	6.445	***	par_43

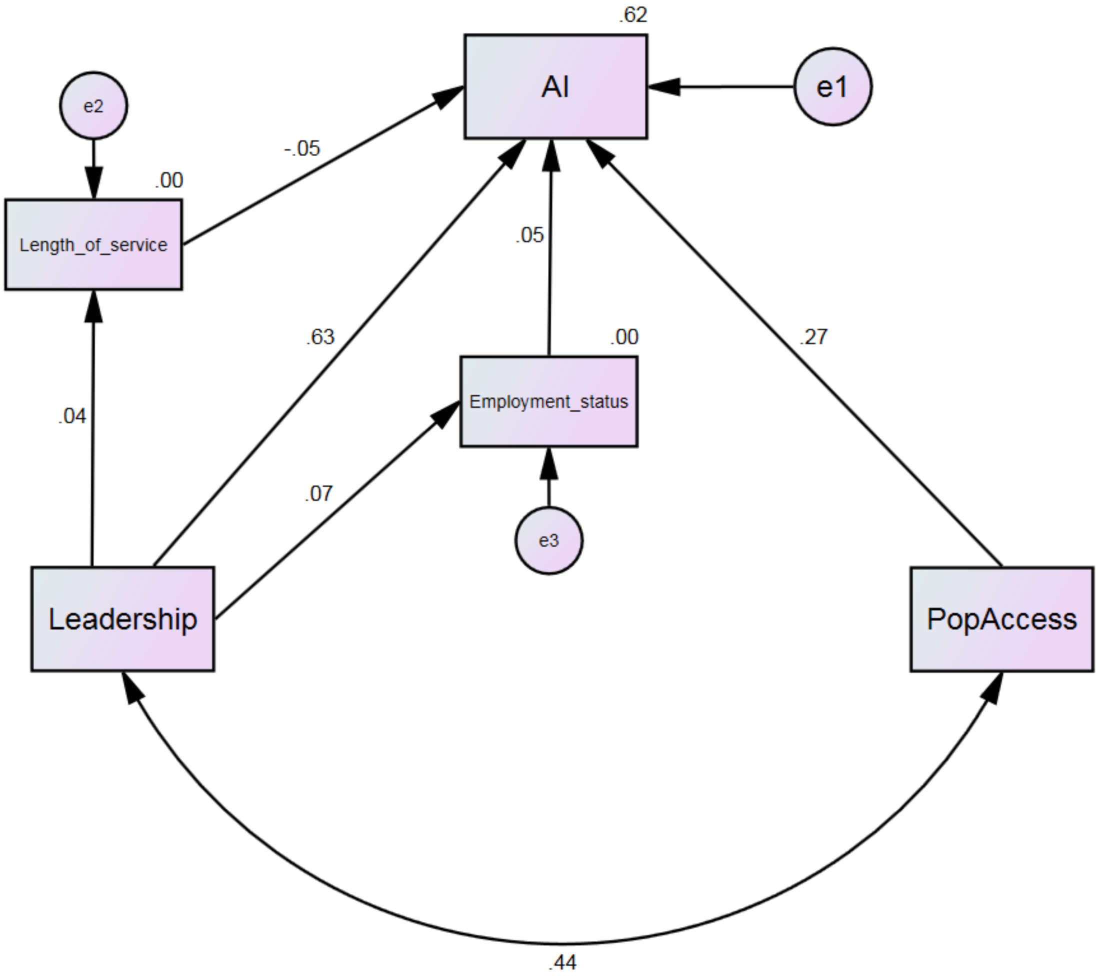
9.6 Appendix F: Structural Model

Regression Weights

Regression Weights: (Group number 1 - Default model)							
			Estimate	S.E.	C.R.	P	Label
AI	<---	Leadership	0.922	0.139	6.636	***	par_1
AI	<---	SkillsGap	-0.61	0.207	-2.939	0.003	par_2
AI	<---	EmpAtt	0.231	0.083	2.778	0.005	par_3
AI	<---	PopAccess	0.264	0.045	5.877	***	par_4

Regression Weights: (Group number 1 - Default model)							
			Estimate	S.E.	C.R.	P	Label
Length_of_service	<---	Leadership	0.043	0.089	0.48	0.631	par_4
Employment_status	<---	Leadership	0.016	0.017	0.945	0.345	par_6
AI	<---	Leadership	0.615	0.05	12.41	***	par_1
AI	<---	PopAccess	0.232	0.043	5.419	***	par_2
AI	<---	Length_of_service	-0.039	0.037	-1.042	0.297	par_5
AI	<---	Employment_status	0.216	0.189	1.142	0.253	par_7

Structural Model 2 – Standardised



9.7 Appendix G: Regression Model

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.799[a]	0.639	0.629	0.55532	0.639	63.367	5	179	0.000	1.749

a. Predictors: (Constant), EmpAtt, Cost, PopAccess, Leadership, SkillsGap

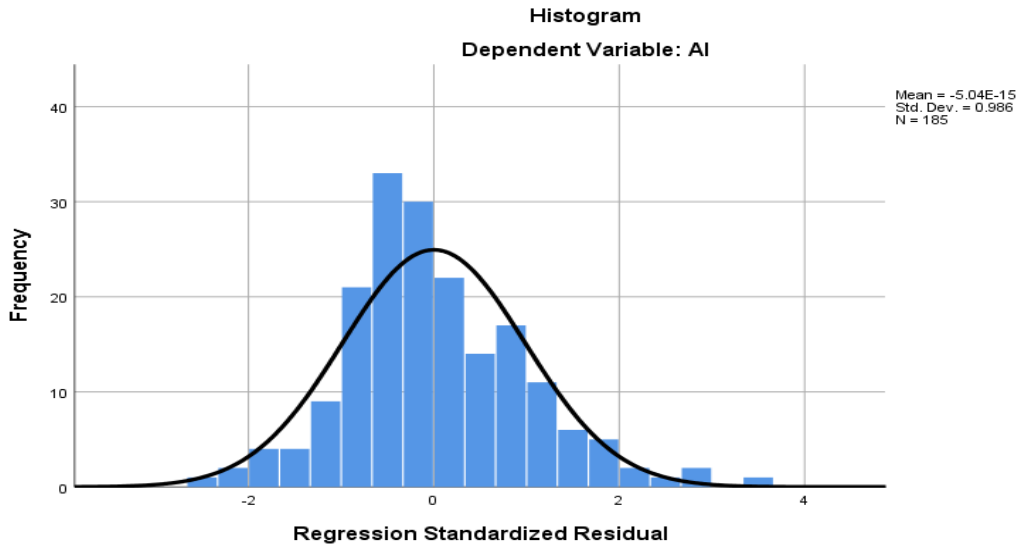
b. Dependent Variable: AI

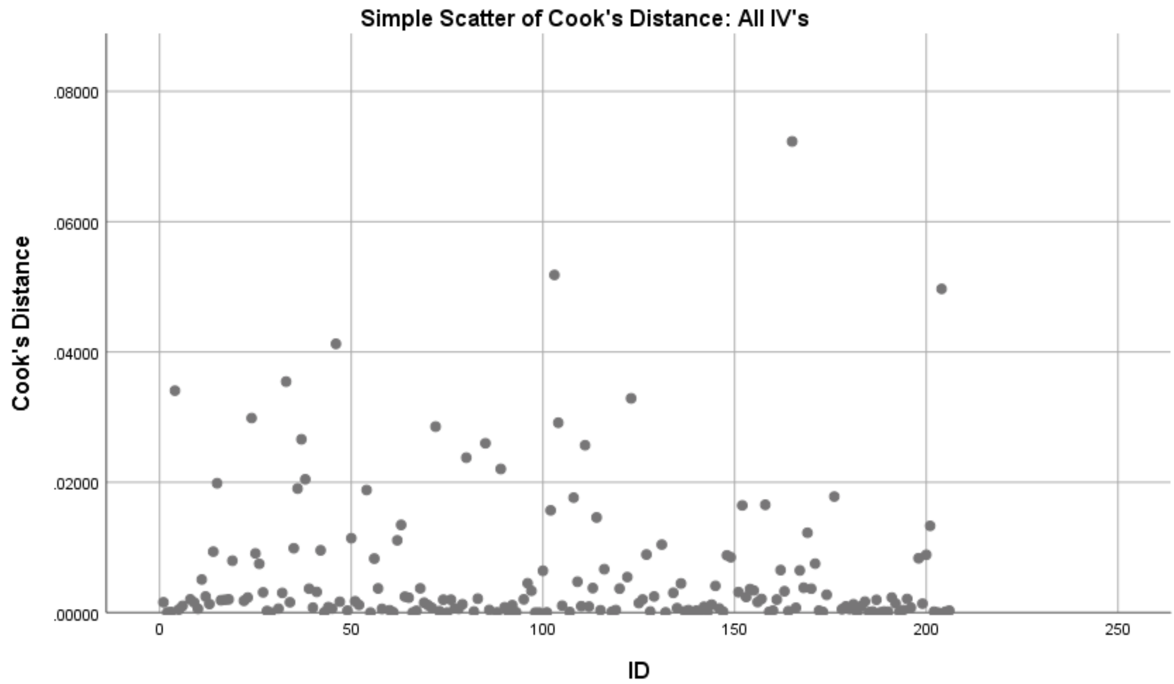
ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	97.707	5	19.541	63.367	.000[b]
	Residual	55.201	179	0.308		
	Total	152.907	184			

a. Dependent Variable: AI

b. Predictors: (Constant), EmpAtt, Cost, PopAccess, Leadership, SkillsGap





Regression Model After Employee Skills Level Variable Removed

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.789[a]	0.623	0.614	0.56625	0.623	74.219	4	180	0.000	1.827

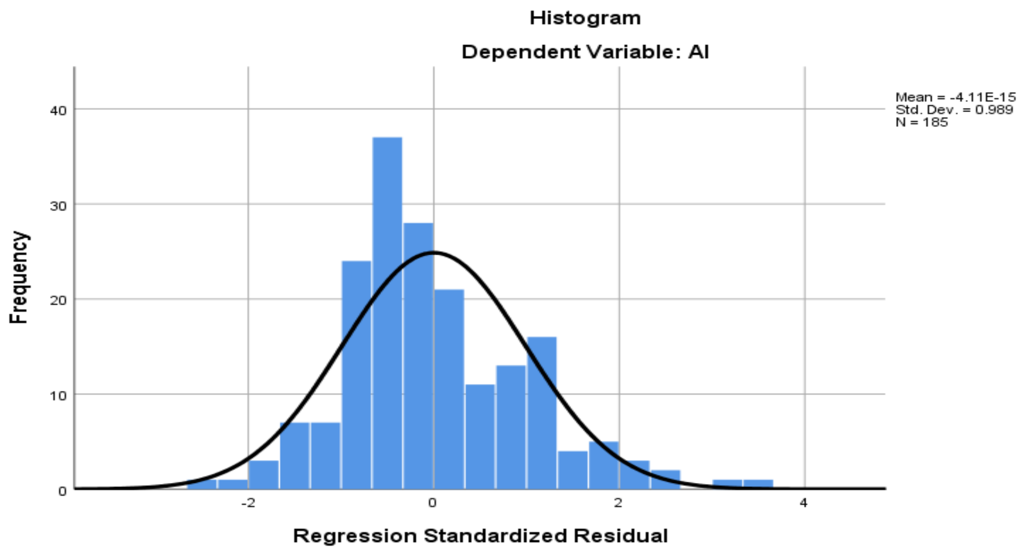
a. Predictors: (Constant), EmpAtt, Cost, PopAccess, Leadership

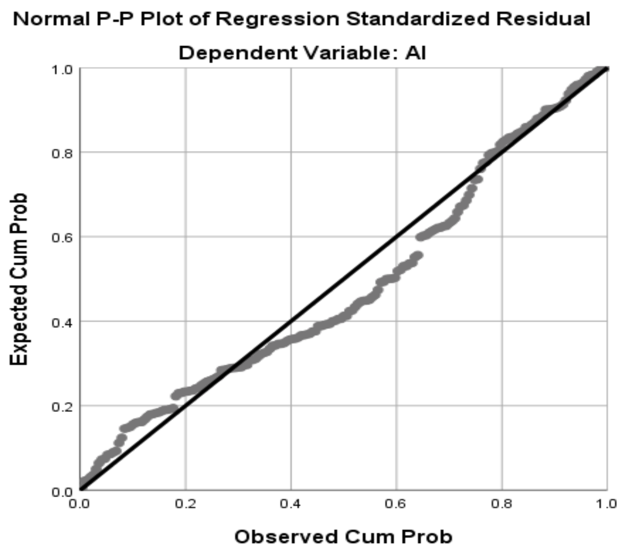
b. Dependent Variable: AI

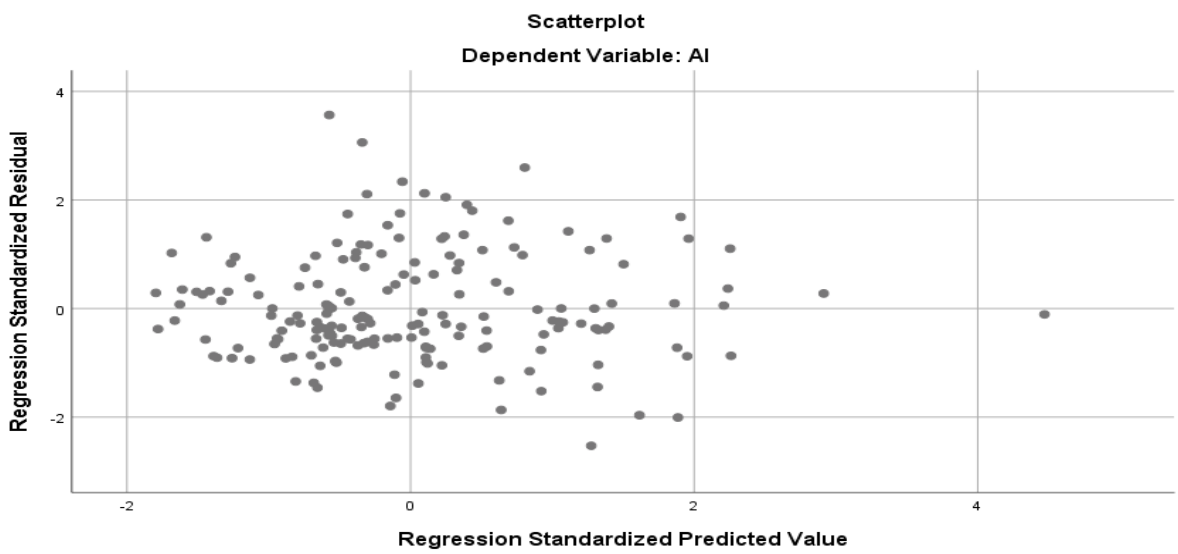
Coefficients[a]

Model		Unstandardized Coefficients		d Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower	Upper	Tolerance	VIF
1	(Constant)	0.297	0.152		1.957	0.052	-0.002	0.596		
	Cost	0.043	0.040	0.053	1.090	0.277	-0.035	0.121	0.902	1.108
	Leadership	0.579	0.073	0.589	7.928	0.000	0.435	0.724	0.379	2.636
	PopAccess	0.209	0.046	0.247	4.581	0.000	0.119	0.299	0.721	1.387
	EmpAtt	0.046	0.059	0.059	0.789	0.431	-0.070	0.163	0.375	2.668

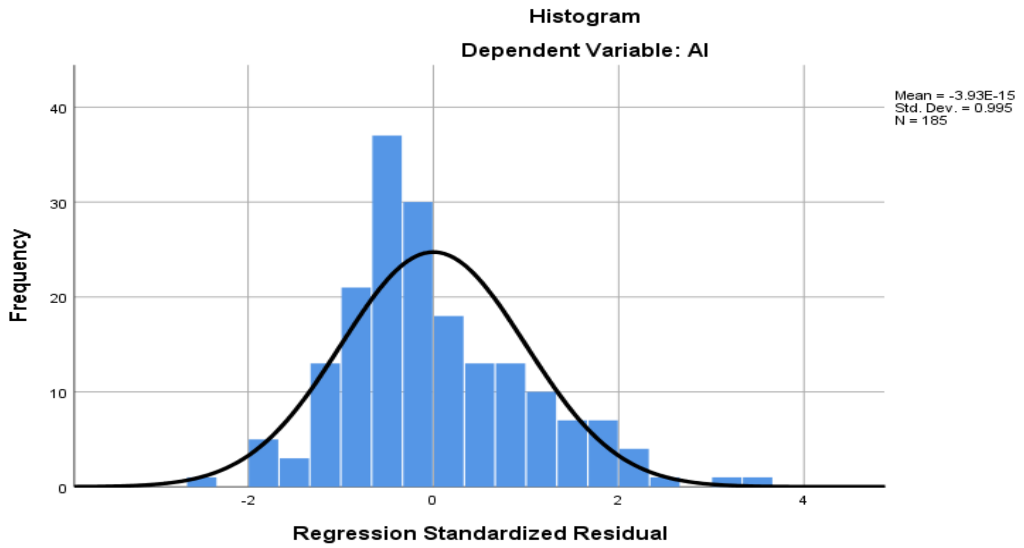
a. Dependent Variable: AI

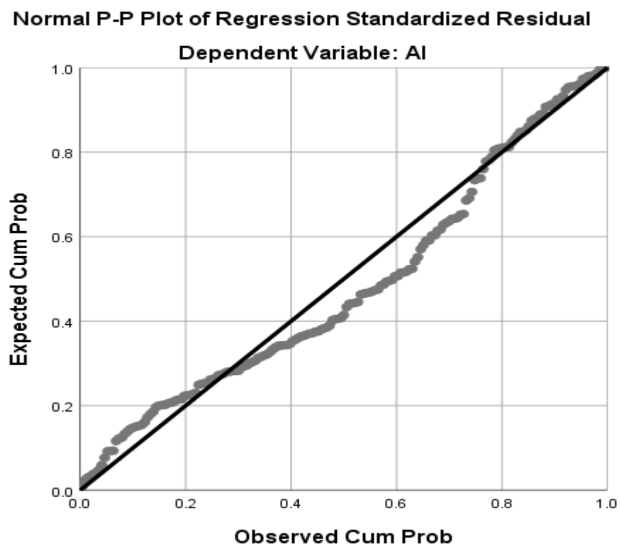

Histogram
Dependent Variable: AI
Mean = -4.11E-15
Std. Dev. = 0.989
N = 185
Frequency
Regression Standardized Residual

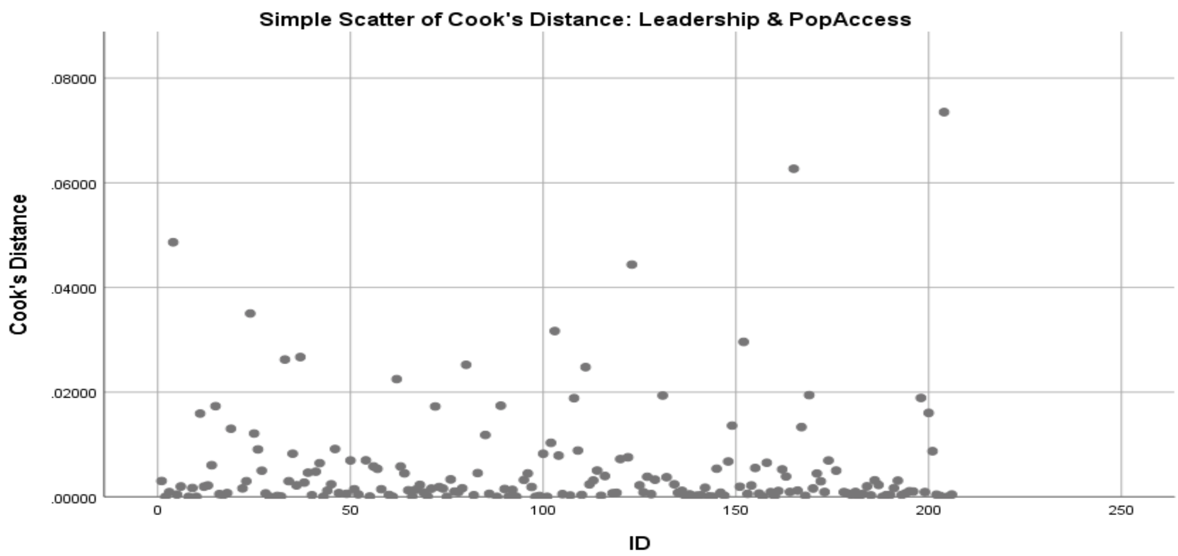

Normal P-P Plot of Regression Standardized Residual
Dependent Variable: AI
Expected Cum Prob
Observed Cum Prob


Scatterplot
Dependent Variable: AI
Regression Standardized Residual
Regression Standardized Predicted Value

Final Regression Model Histogram/G Graph







9.8 Appendix H: Turnitin Report

Dear Akayombokwa Mutumba,

You have successfully submitted the file "Final Draft - Thesis" to the assignment "Test your originality" in the class "GIBS Information Centre 2018 _2880_1" on 06-Nov-2018 12:06PM (UTC+0200). Your submission id is 959938299. Your full digital receipt can be downloaded from the download button in your class assignment list in Turnitin or from the print/download button in the document viewer.

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Final Draft - Thesis

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