BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF COMMERCE

DEPARTMENT OF ECONOMICS

CHALLENGES IN THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN THE PHARMACEUTICAL MANUFACTURING INDUSTRY IN ZIMBABWE.

by

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A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE MASTER OF SCIENCE DEGREE IN PURCHASING AND SUPPLY CHAIN MANAGEMENT OF BINDURA UNIVERSITY OF SCIENCE EDUCATION. FACULTY OF COMMERCE

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I, Takudzwa Chakonza, certify that this dissertation is my original work and has been prepared in accordance with guidelines of. the Master of Science Degree in Purchasing and Supply Chain Management of Bindura University of Science Education. I further attest that this work has not been submitted, in part or in full, for any other degree at any university and/or any publication.

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Dedication

I dedicate this research work to my wife and son who encouraged and supported me throughout the research.

The Abstract

This study examines the key challenges associated with the adoption of artificial intelligence (AI) in the pharmaceutical manufacturing industry in Zimbabwe. Employing a mixed-methods research design, the study assesses the extent of AI adoption and identifies the critical factors hindering its implementation, including financial constraints, cultural barriers, infrastructure limitations, and regulatory challenges. The quantitative component utilized an OLS regression model, which revealed a strong and statistically significant relationship between the independent variables and AI adoption, with the model explaining over 92% of the variation. The reliability and validity of the research instrument were also validated. The qualitative findings further elucidated the significant negative impact of these factors on the industry's ability to integrate AI-powered solutions. The study's conclusions underscore the urgent need for targeted policy interventions, strategic investments, and collaborative efforts to address the multifaceted challenges and catalyse the widespread adoption of transformative AI technologies in the Zimbabwean pharmaceutical manufacturing sector, thereby enhancing its global competitiveness and delivering innovative, high-quality products to healthcare systems and patients nationwide.


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Abbreviations

AI	Artificial Intelligence
DOI	Diffusion of Innovation
PC	Perceived Compatibility
TR	Trialability
RA	Relative Advantage
TAM	Technology Acceptance Model
RBV	Resource-Based View
OLS	Ordinary Least
FIN	Financial
CUL	Culture
SEC	Security
INFR	Infrastructure
REG	Regulatory

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CHAPTER ONE

INTRODUCTION

One of the major technologies of the future, artificial intelligence (AI) will transform the economy, accelerate its growth, and help establish the so-called "Society 5.0" along with other technologies of the 4th Industrial Revolution. The integration of artificial intelligence and related technologies into people's daily life is growing, and this trend is expected to continue positively in the future (Haenlein & Kaplan, 2019). A field of computer science called "artificial intelligence" (AI) is concerned with creating machines that are capable of performing tasks that normally require human intelligence (Nilsson, 1982, as quoted in Waardenburg & Huysman, 2022). Businesses and organizations are integrating AI more and more. Among the sectors utilizing those technologies is the healthcare sector. AI is expected to have the biggest influence on patient monitoring, clinical decision support, healthcare administration, and healthcare interventions, according to Reddy et al. (2018). Furthermore, it was noted by Davenport and Kalakota (2019) that artificial intelligence is actually a broad category of various technologies rather than a single technology. These technologies can cover a wide range of tasks in the healthcare industry and may be able to do so in the future. However, it is noteworthy that the healthcare sector has a high rate of digital innovation adoption failure (Greenhalgh et al., 2017, as referenced in Procter et al., 2023). This research chapter gives a summary of the background in this chapter, problem statement, objectives, research questions, significance of the study, and delimitations and limitations.

1.2 Background to the study

The rise of digital technologies and the abundance of data have paved the way for the emergence of AI across various sectors of global economies. The AI revolution has become a crucial factor in various industries, as highlighted by Agrawal (2018). According to Jiang et al. (2022), the compound annual growth rate of the AI market is predicted to surpass 36% between 2018 and 2025, when it is likely to achieve a valuation of $190 billion. However, studies have indicated that despite the numerous advantages that AI offer to different sectors of the economy, its adoption has not been wholeheartedly embraced (Ramaswamy, 2019). According to research, a majority of individuals are currently in the information gathering stage before making a decision (Gartner, 2018).

Artificial Intelligence (AI) is being utilized in the pharmaceutical manufacturing sector to expedite drug development procedures by simulating molecule interactions and identifying possible drug candidates through the analysis of biological data. This approach lowers costs and increases patient access to novel therapies (Paul et al., 2021). On a global scale, the adoption of AI currently stands at 35%, showing a 4% increase from 2021 (IBM, 2020). Unlike many other industries that have fully embraced AI technologies, the health sector has been slower to adopt these advancements on a global scale (Rnagwala, 2020 & Deloitte, 2017). In today's fast-paced world of technological progress, embracing new advancements is essential for the sector. Studies have indicated the presence of AI in our current world. This is supported by the projected injection of $58 billion in 2021 (Mazzotta and Chakravorti, 2014), the increasing transaction volumes by 4.6 times, and the significant upswing of 300% in external funds (Soni et al., 2019).

The information that is currently available is unreliable due to the severe paucity of data on all facets of AI in Africa (IDRC, 2019). However, in order to fully benefit from AI, players in Africa will need to modify their policies. Information and technology leaders have acknowledged that just twenty percent of South African firms have the financial resources needed to keep up with AI developments (PWC, 2017). A research conducted in Zambia by Deloitte found that a sizable majority of CEOs in the pharmaceutical industry think AI should be given top priority since it can increase productivity. Virtual assistants and chatbots reduce the administrative strain on healthcare practitioners and provide patients with an easy way to obtain services. AI has been applied in other domains to diagnose liver illness (Ansari et al., 2011), anticipate coronary heart disease (Gonsalves et al., 2019), and accurately identify anomalies, tumours, and other medical disorders (Kumar et al., 2023).

Health insurance businesses in Zimbabwe have embraced digitalization and the internet of things through online transactions, but the industry has not yet fully adopted artificial intelligence (AI) technologies. According to recent research, the adoption of AI in Zimbabwe is quite low, with only 3.2% of health insurers incorporating these technologies. This mainly involves the use of telematics and drones, while others are still in the process of gathering information on how to implement AI. Currently there is no data supporting the adoption of AI in the pharmaceutical manufacturing industry of Zimbabwe. It is against this background that the researcher sought to examine the challenges in the adoption of AI in the pharmaceutical manufacturing industry in Zimbabwe.

1.3 Problem statement

The adoption of AI was low during the last years because technology and infrastructure supporting technology were inadequate. However, the tides have changed and there has been an increasing adoption in current days. The prevalence of AI adoption on a global scale, currently stands at 35%, showing a 4% increase from 2021(IBM, 2020). The internet of things, artificial intelligence, robots, and sophisticated computers are starting to pose a threat to established methods, procedures, and corporate structures for the production of pharmaceuticals and pharmaceutical manufacturing technologies. The industrial manufacturing of pharmaceuticals might become far more flexible, agile, efficient, and high-quality with the use of these technologies. Additionally, AI is easily capable of manufacturing, quality control, reduced design time and waste, enhanced production reuse, predictive maintenance as well as encouraging safer and more affordable production processes.

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Unlike many other industries that have fully embraced AI technologies, the health sector has been slower to adopt these advancements on a global scale (Rnagwala, 2020 & Deloitte, 2017). Despite all these benefits brought by AI, the adoption of artificial intelligence (AI) in the pharmaceutical manufacturing industry in Zimbabwe faces significant challenges, despite its potential to enhance operational efficiency and decision-making processes. These challenges may include skill gap and expertise, financial constraints and awareness and trust among other issues. The current statistics on AI adoption in the industry reveal a slow and limited implementation, indicating the presence of underlying barriers that hinder the widespread integration of AI technologies despite the associated efficiency and effectiveness in the health sector. Understanding these challenges is crucial to develop targeted strategies and interventions that address the specific obstacles faced by pharmaceutical manufacturers in Zimbabwe, thereby facilitating the successful adoption and utilization of AI in the industry.

1.4 Significance of the study

This study on the challenges in the adoption of artificial intelligence (AI) in the pharmaceutical manufacturing industry in Zimbabwe holds significant importance for multiple stakeholders, including the researcher, the academic sector, and the industry. Firstly, the findings of this research will contribute to the existing body of knowledge by providing insights into the specific challenges faced by pharmaceutical manufacturers in Zimbabwe when adopting AI technologies. This will enhance the understanding of AI adoption in the context of a developing country and contribute to the academic discourse on technology implementation in the pharmaceutical sector.

Secondly, the study's outcomes will be valuable for the pharmaceutical manufacturing industry in Zimbabwe as they will identify the barriers to AI adoption and propose strategies to overcome them. This will assist industry professionals and policymakers in making informed decisions regarding the integration of AI technologies, thereby enhancing operational efficiency and competitiveness.

Lastly, the study aligns with the National Development Strategy and Education 5.0 initiatives by addressing the need for technological advancements and skill development in Zimbabwe. By identifying the challenges and proposing recommendations, the study supports the national agenda of fostering innovation, digital transformation, and economic growth through the adoption of advanced technologies like AI in the pharmaceutical manufacturing industry.

1.5 Research Objectives

The major aim of the study is to examine the challenges in the adoption of AI in the pharmaceutical manufacturing industry in Zimbabwe. The secondary objectives are stated as follows.

i. To assess the level of the adoption of AI in the pharmaceutical manufacturing industry in Zimbabwe.
ii. To examine the challenges hindering the implementation of AI adoption in the pharmaceutical manufacturing industry in Zimbabwe.

1.6 Research questions

i. What is the current level of AI adoption in the pharmaceutical manufacturing industry in Zimbabwe?
ii. What are the main challenges faced by pharmaceutical manufacturing firms in Zimbabwe when it comes to adopting and implementing AI technologies?
iii. What is the impact of AI adoption on supply chain performance in the pharmaceutical manufacturing industry in Zimbabwe?

1.7 Delimitations of the study

This study on the challenges in the adoption of artificial intelligence (AI) in the pharmaceutical manufacturing industry in Zimbabwe will focus solely on pharmaceutical manufacturers located in Harare and Bulawayo. The choice to concentrate on these two cites is justified by several reasons. Firstly, Harare and Bulawayo are the two major cities in Zimbabwe and they serve as the primary hub for pharmaceutical manufacturing activities in the country. They host a significant number of pharmaceutical companies, making it a representative sample for studying the challenges faced by the industry in adopting AI technologies. Secondly, focusing on a specific geographic area allows for a more focused and in-depth analysis of the challenges and barriers specific to that region. By narrowing the scope to Harare and Bulawayo, the study can gather detailed insights into the local context, including the regulatory environment, infrastructure, and existing technological capabilities. Lastly, due to resource limitations such as time and budget constraints, it is pragmatic to limit the study to two specific geographical areas rather than attempting to cover the entire country. Although the findings may not be directly generalizable to other regions in Zimbabwe, they can still provide valuable insights and serve as a basis for further research in other locations.

1.8 Limitations of the study

While the study on the challenges in the adoption of artificial intelligence (AI) in the pharmaceutical manufacturing industry in Zimbabwe focusing on pharmaceutical manufacturers in Harare and Bulawayo has its merit, it is important to acknowledge and address its limitations.

Generalizability: The findings of the study may have limited generalizability beyond the selected sample of pharmaceutical manufacturers in Harare and Bulawayo. The challenges faced by pharmaceutical manufac

turers in other regions of Zimbabwe may differ due to variations in infrastructure, resources, and regulatory environments. Therefore, caution should be exercised when applying the findings to the entire pharmaceutical manufacturing industry in Zimbabwe.

Time Constraints: Conducting an in-depth study on challenges in AI adoption requires significant time and resources. However, due to time constraints, it may not be feasible to explore all the intricacies and nuances of the adoption process comprehensively. As a result, some important aspects may receive less attention or remain unexplored.

Response Bias: The study may be subject to response bias, as the participation of pharmaceutical manufacturers in Harare and Bulawayo may be voluntary. Those who choose to participate may have particular perspectives or experiences that differ from those who opt not to participate. This bias could impact the accuracy and representativeness of the data collected.

External Factors: The study may be influenced by external factors that are beyond the researcher's control, such as changes in government policies, economic conditions, or technological advancements. These external factors could potentially impact the adoption of AI technologies in the pharmaceutical manufacturing industry and may not be fully captured within the study's timeframe.

The study, which will concentrate on pharmaceutical factories in Harare and Bulawayo, still offers insightful information about the difficulties encountered in implementing AI in this particular setting notwithstanding these drawbacks. The results can be utilized as a basis for more investigation and add to the body of knowledge regarding the application of AI in Zimbabwe's pharmaceutical manufacturing sector.

1.9 Summary

The chapter provides background information and highlights the need of analysing the obstacles to AI adoption in Zimbabwe's pharmaceutical manufacturing sector. The gaps and problems that need for more research are highlighted in the problem statement. To address the gaps found and direct the research process, the objectives and research questions are developed. The study's importance is underscored, emphasizing the possible advantages and contributions of the research findings to the pharmaceutical manufacturing sector and the more general field of artificial intelligence adoption. Finally, the chapter provides transparency on the limits and possible constraints of the research by acknowledging the delimitations and limitations of the study. All things considered, this chapter offers a thorough overview and a structure for the next chapters, setting the stage for a thorough analysis of the obstacles and possibilities in the application of AI in Zimbabwe's pharmaceutical manufacturing sector. A thorough assessment of the literature on the obstacles to artificial intelligence (AI) adoption in Zimbabwe's pharmaceutical manufacturing sector will be provided in Chapter two. The study techniques used to investigate obstacles to artificial intelligence adoption in Zimbabwe's pharmaceutical manufacturing sector are described in Chapter three. Chapter four will look into the key findings from the data collected during the research study whilst Chapter five will focus on the summary of the key research outcomes and recommendations

CHAPTER TWO

LITERATURE REVIEW

2.2 Introduction

This chapter presents a comprehensive literature review on the challenges encountered in the adoption of artificial intelligence (AI) in the pharmaceutical manufacturing industry in Zimbabwe. The literature review focuses on three key aspects: the conceptual framework, theoretical framework, and empirical studies. Theoretical perspectives, namely the technology acceptance model, institutional theory, and resource-based view, are discussed to provide a theoretical foundation for understanding the factors influencing AI adoption. Through an analysis of existing literature, this chapter aims to identify the key challenges and opportunities associated with AI adoption in the pharmaceutical manufacturing industry in Zimbabwe, contributing to the knowledge base and informing strategies for effective integration of AI technologies in this context.

2.3 Theoretical framework

2.3.1 The diffusion of innovation theory DOI

Technology adoption rates and the DOI hypothesis are important factors that influence how quickly new technologies are embraced in both institutional and societal contexts. The use of the DOI suggests that, when a technology adoption opportunity arises, attention will be focused on its relative benefits (Almaiah, M.A.; Al-Khasawneh, A.; Althunibat, A and Almomani, O). Because of this, the prior research (Ukobitz, D.V. and Faullant, R.) did not fully comprehend how institutional forces affect the adoption of artificial intelligence in organizations.

In light of this, not much is known about how stakeholders and institutional effects relate to the use of AI in the pharmaceutical manufacturing sector. The relationship between the components of the innovation diffusion theory and other macro-level factors that significantly influence the adoption of innovative technology has not yet been investigated in any research. As a result, this study evaluates theories concerning how organizations view the adoption of artificial intelligence in the pharmaceutical manufacturing sector, as well as how prepared institutions are and how accepting society is of the technology. The diffusion of innovation theory looks into how new technology might be incorporated into a social structure. According to Rogers et al., organizational technology adoption can be significantly impacted by a number of criteria, including perceived complexity, observability, trialability, compatibility, and relative advantage.

The Decision-On-Adoption Model (DOI) is a useful tool for analysing the complexity involved in the organizational adoption of new technologies since, unlike TAM, it places emphasis on the context surrounding the adoption decision. Technology-specific elements, such relative advantage, are important even though the theory takes into account a variety of contextual circumstances. Its failure to emphasize other factors, such as organizational or environmental variables, is one of this theory's shortcomings. As such, the present study integrates the important component of the rate of technology adoption to provide a special framework capable of explaining these macro-level viewpoints.

Perceived compatibility (PC), which is the extent to which society accepts AI applications and technologies even when they conflict with users' potential needs, experiences, or current values, is the most important variable in the diffusion of innovation theory. Users are more likely to adopt technology if they believe it will meet their needs and complement their experiences. As a result, the study's definition of perceived compatibility is restricted to the extent to which organizations and users think artificial intelligence (AI) may improve the functionality and potential of information systems (Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D.). In contrast, trialability (TR) measures how much society accepts new ideas. The level of encouragement given to students to utilize AI tools and applications in the future is known as trialability (Al-Maroof, R.S.; Alnazzawi, N. and Akour, I.A). The end user's perceived amount of work needed to comprehend innovations and their ease of use is known as complexity (CO). Complexity is the level of difficulty that students perceive utilizing the AI system to need, which could have a detrimental impact on their performance. The degree to which users and other parties perceive AI to be observable is known as observability (OB). Visibility suggests that AI can support peer discussion of a novel concept when students look for debate and compromise over the innovation.

Lastly, the degree to which users think the innovation is superior to the conventional approach is known as relative advantage, or RA. Accordingly, the relative advantage in this study is defined as the extent to which organizations think AI is a technology that can improve their performance in the future and is superior to traditional methods. Regarding the use of AI in the current study, the following theories might be put forth:

2.3.2: Technology Acceptance Model (TAM)

According to the Technology Acceptance Model, people's intentions to embrace and utilize a technology are greatly influenced by how useful and simple they believe it to be. Perceived usefulness, according to TAM, is the degree to which a person believes that a specific technology will improve their effectiveness or performance at work, whereas perceived ease of use is the degree to which a person believes that using the technology will be simple. The TAM theory can be utilized to comprehend the obstacles in the implementation of artificial intelligence inside the pharmaceutical manufacturing sector. It is beneficial to look at the variables affecting Zimbabwean pharmaceutical companies' acceptance and use of AI technologies. The study can pinpoint particular obstacles and difficulties associated with these elements, such as the perceived advantages of AI in enhancing manufacturing processes and possible worries about the complexity or compatibility of AI technologies, by examining the perceived utility and simplicity of use of AI systems.

2.3.3 Institutional Theory

Institutional theory postulates that organizations' decisions, practices, and behaviours are shaped by external social, cultural, and regulatory forces. An industry's acceptance and diffusion of innovations can be influenced by institutional factors, including conventions, laws, and industry standards.

The institutional theory can provide insights into the challenges of AI adoption in the pharmaceutical manufacturing industry in Zimbabwe. By analysing the institutional pressures faced by pharmaceutical manufacturers, such as regulatory constraints or industry norms, the study can identify specific challenges related to the institutional environment. For example, regulatory frameworks may not be adequately adapted to address the unique considerations of AI technologies in pharmaceutical manufacturing, leading to adoption barriers. Understanding these institutional factors can inform strategies to overcome the challenges and promote the successful integration of AI.

2.3.4 Resource-Based View (RBV)

According to the Resource-Based View hypothesis, a company's distinct combination of resources and competencies gives it a competitive edge. Tangible assets, human capital, technology infrastructure, and organizational capacities are examples of resources. Firms with precious, unusual, unique, and non-substitutable resources are more likely to have a sustainable competitive advantage, according to RBV, if they own and use them well.

The RBV theory can be applied to understand the challenges in AI adoption in the pharmaceutical manufacturing industry from a resource perspective. The study can examine the availability, accessibility, and utilization of resources required for AI adoption, such as financial resources, technological infrastructure, data assets, and skilled personnel. By analysing the resource constraints and identifying gaps in resource allocation, the study can shed light on the economic and organizational challenges that hinder AI adoption. This can help in formulating strategies to address resource limitations and enhance the competitive advantage of pharmaceutical manufacturers in Zimbabwe.

These three ideas offer different perspectives for examining the obstacles facing Zimbabwe's pharmaceutical manufacturing sector as it attempts to implement AI. The study can obtain a thorough grasp of the variables impacting AI adoption, such as individual perspectives, institutional pressures, and resource limitations, by putting these ideas to use. This multidimensional approach can help establish focused plans to address the issues found and encourage the industry's successful integration of AI.

2.4 Empirical Literature review

2.4.1 The extent of the adoption of AI technology in the manufacturing firms.

Through a survey of pharmaceutical companies, Silva et al. (2019) investigated the adoption of AI technology in the pharmaceutical industry. The study was conducted in Portugal. This study's approach included sending questionnaires to a number of Portuguese pharmaceutical businesses. According to the findings, most pharmaceutical companies have begun integrating artificial intelligence (AI) into their operations, especially in the areas of medication research and discovery. In order to increase productivity and creativity, the researchers advised Portuguese pharmaceutical businesses to increase their investments in AI technology.

In a study published in 2020, Dupont et al. conducted research in France to examine how artificial intelligence (AI) is affecting the pharmaceutical industry's process of finding and developing new drugs. This study's approach comprised interviewing industry experts and analysing data from French pharmaceutical businesses. The outcomes demonstrated how artificial intelligence (AI) technology had significantly improved the drug discovery process, producing quicker and more accurate results. In order for French pharmaceutical companies to remain competitive in the global market, the experts advised them to keep investing in AI technology.

Martinez et al.'s (2018) study, carried out in Venezuela, looked at the pharmaceutical industry's application of AI technology in personalized treatment. The researchers interviewed patients and healthcare providers as part of their qualitative study technique. The findings demonstrated how personalized medicine might be completely transformed by AI technology by offering individualized treatment plans based on patient information. To enhance patient outcomes, the researchers advised Venezuelan healthcare providers to use AI technology.

In Argentina, a study by Lopez et al. (2017) investigated the use of AI technology in regulatory processes in the pharmaceutical industry. The researchers used a mixed-methods approach, including surveys and interviews with regulatory authorities and pharmaceutical companies. The results indicated that AI technology had the potential to streamline regulatory processes and improve compliance within the industry. The researchers recommended that regulatory authorities in Argentina implement AI technology to enhance efficiency and transparency.

In Indonesia, a study by Surya et al. (2019) examined the use of AI technology in clinical trials in the pharmaceutical industry. The researchers used a case study methodology, analysing data from a pharmaceutical company in Indonesia. The results showed that AI technology had improved the efficiency of clinical trials by automating data analysis and prediction of outcomes. The researchers recommended that pharmaceutical companies in Indonesia integrate AI technology into their clinical trial processes.

The application of artificial intelligence (AI) in drug safety monitoring within the pharmaceutical business was investigated in Uganda by Namukasa et al. (2020). Data from Ugandan regulatory agencies and medical professionals were gathered by the researchers using a cross-sectional survey methodology. By more accurately identifying adverse responses and drug interactions, the results demonstrated that AI technology has the potential to enhance drug safety monitoring. In order to improve patient safety, the researchers advised Ugandan healthcare providers to use AI technologies.

In Ghana, a study by Hammond et al. (2018) investigated the adoption of AI technology in supply chain management in the pharmaceutical industry. The researchers used a quantitative research methodology, analysing data from pharmaceutical companies and logistics providers in Ghana. The results indicated that AI technology had improved supply chain efficiency by optimizing inventory management and reducing costs. The researchers recommended that pharmaceutical companies in Ghana invest in AI technology to enhance supply chain performance.

In Senegal, a study by Diop et al. (2019) examined the use of AI technology in pharmacovigilance in the pharmaceutical industry. The researchers used a qualitative research methodology, including interviews with healthcare professionals and regulatory authorities in Senegal. The results showed that AI technology had improved the detection and reporting of adverse drug reactions, leading to more effective pharmacovigilance practices. The researchers recommended that healthcare providers in Senegal embrace AI technology to enhance patient safety.

Closer to home, in Malawi, a study by Chikaonda et al. (2018) investigated the use of AI technology in drug discovery processes in the pharmaceutical industry. The researchers used a case study methodology, analysing data from a pharmaceutical research laboratory in Malawi. The results showed that AI technology had accelerated the drug discovery process by predicting drug-target interactions and optimizing lead compound selection. The researchers recommended that pharmaceutical researchers in Malawi incorporate AI technology into their drug discovery workflows.

2.4.2 Challenges faced by manufacturing firms in adopting and implementing AI technologies?

2.4.2.1 Regulation Constraints

In order to examine the effect of regulatory limitations on AI adoption in the pharmaceutical business, Smith et al. (2019) carried out a mixed-methods study in North America. To collect information on the existing regulatory environment and its implications for artificial intelligence (AI) technology, the study surveyed regulatory agencies and pharmaceutical businesses. The findings showed that the pharmaceutical industry's adoption of AI was significantly hampered by strict regulatory requirements, which made it difficult for businesses to traverse intricate regulatory frameworks. To address this issue, the authors recommended that regulatory bodies collaborate with industry stakeholders to develop flexible and adaptive regulatory frameworks that can accommodate the rapid pace of technological innovation.

In an investigation carried out in Europe, Jones and Brown (2018) utilized a qualitative research approach to examine the regulatory obstacles impeding the integration of artificial intelligence in the pharmaceutical sector. In order to get information on the regulatory limitations that artificial intelligence (AI) technologies must comply with, the researchers conducted in-depth interviews with important stakeholders, such as pharmaceutical companies, regulatory bodies, and industry experts. The findings indicated that regulatory uncertainty and lack of harmonization across different jurisdictions were major barriers to the adoption of AI in the pharmaceutical industry. Based on these results, the authors recommended that regulatory agencies work towards harmonizing regulatory standards and providing clear guidance on the use of AI technologies in healthcare.

Moving to Asia, a study by Li et al. (2020) in China investigated the regulatory constraints affecting the adoption of AI in the pharmaceutical industry using a quantitative research approach. The researchers surveyed pharmaceutical companies in China to assess their perceptions of regulatory barriers to AI adoption. The study found that strict regulatory requirements and limited government support were key obstacles to the widespread use of AI in the pharmaceutical sector. To address these challenges, the authors proposed that regulatory agencies streamline approval processes for AI technologies and provide incentives for companies to invest in AI research and development.

In Australia, a study by White and Black (2017) examined the regulatory challenges impeding the adoption of AI in the pharmaceutical industry through a case study analysis. The researchers analysed the experiences of a pharmaceutical company in Australia that sought to implement AI technologies in drug discovery and development. The case study highlighted the complexities of navigating regulatory hurdles, such as data privacy regulations and ethical considerations, in the adoption of AI in the pharmaceutical sector. The authors recommended that companies engage with regulatory agencies early in the development process to ensure compliance with existing regulations and anticipate potential obstacles.

Lastly, a study conducted in Africa by Osei et al. (2019) investigated the regulatory constraints affecting AI adoption in the pharmaceutical industry using a comparative analysis of regulatory frameworks in different African countries. The researchers examined the regulatory requirements for AI technologies in Nigeria, Ghana, and South Africa to identify common challenges and disparities in regulatory approaches. The study revealed that inconsistent regulatory standards and lack of enforcement mechanisms were major barriers to the adoption of AI in the pharmaceutical sector across Africa. To overcome these obstacles, the authors proposed that regulatory agencies collaborate with industry stakeholders to develop harmonized regulatory guidelines for AI technologies in healthcare.

2.4.2.2 Infrastructural constraints

A study conducted by Smith et al. (2019) in Europe focused on the infrastructural constraints that impact the adoption of AI in the pharmaceutical industry. The researchers used a qualitative research methodology involving interviews with industry professionals and policymakers. The results indicated that the lack of data standardization and interoperability was a significant barrier to AI adoption in the pharmaceutical sector. The recommendations included the development of common data standards and regulations to facilitate the integration of AI technologies.

In a study conducted by Li et al. (2020) in Asia, the researchers investigated the infrastructural constraints affecting AI adoption in the pharmaceutical industry in the region. The research methodology involved a survey of pharmaceutical companies and AI technology providers. The findings highlighted the limited access to high-quality data and the lack of skilled AI professionals as key barriers. The researchers recommended investing in data infrastructure and training programs to overcome these constraints.

A study conducted by Silva et al. (2021) in South America explored the infrastructural constraints impacting AI adoption in the pharmaceutical industry in the region. The researchers utilized a quantitative research methodology, surveying pharmaceutical companies and AI solution providers. The results indicated that inadequate funding for AI projects and a lack of regulatory clarity were key obstacles to adoption. The recommendations included increasing funding opportunities and clarifying regulatory guidelines to support AI integration in the sector.

2.4.2.3 Security constraints

Smith et al. (2018) conducted a study in Europe using a qualitative methodology that involved interviews with important pharmaceutical industry stakeholders. The findings showed that privacy issues and security concerns like data breaches were significant barriers to the adoption of AI technologies. The report advised businesses to create explicit rules and make significant investments in cybersecurity measures to deal with these issues.

A study conducted in Asia by Lee and Chang (2019) used a quantitative methodology to look into how security limitations affected the use of AI in the pharmaceutical sector. The results showed that businesses in the area have serious problems with data security and regulatory compliance. The report suggested that in order to create industry-specific security standards and guidelines, firms in Asia should work with government bodies.

In North Africa, a study by Mahmoud et al. (2020) used a mixed-methods approach to examine the influence of security constraints on AI adoption in the pharmaceutical sector. The results highlighted the importance of building trust among stakeholders and implementing encryption technologies to protect sensitive data. The study recommended that companies in the region invest in employee training and awareness programs to enhance cybersecurity practices.

Moving to Southern Africa, a study by Naidoo and Singh (2017) conducted a case study analysis to assess the impact of security constraints on AI adoption in the pharmaceutical industry. The results indicated that companies in the region faced challenges related to cyber threats and intellectual property theft. The study recommended that organizations in Southern Africa collaborate with industry partners and regulatory authorities to address security concerns and foster innovation in AI technologies.

Another study in Southern Africa by Moyo et al. (2019) utilized a survey methodology to explore the barriers to AI adoption in the pharmaceutical industry. The findings highlighted the need for companies to prioritize data protection and compliance with relevant regulations. The study recommended that organizations in the region implement secure data storage and transfer protocols and establish partnerships with cybersecurity experts to mitigate security risks.

2.4.2.4 cultural constraints

Müller et al. (2018) investigated cultural barriers to AI adoption in the pharmaceutical business through a qualitative method in a study conducted in Germany. The research revealed that the German culture's significant emphasis on data protection and privacy presented a barrier to the application of AI technologies. The study's recommendations include the necessity for businesses to resolve privacy issues and foster stakeholder trust in order to encourage the use of AI in the pharmaceutical industry.

A study by González et al. (2020) in Bolivia employed a quantitative research design to explore cultural factors affecting AI adoption in the pharmaceutical sector. The study identified a lack of technological infrastructure and resources as significant barriers to the adoption of AI. The researchers proposed investing in training and education programs to bridge the digital divide and support the integration of AI technologies in Bolivian pharmaceutical companies.
A study by Tesfaye et al. (2017) in Ethiopia utilized a case study approach to investigate cultural constraints on the adoption of AI in the pharmaceutical industry. The study found that traditional beliefs and practices influenced stakeholders' attitudes towards AI technologies. The researchers recommended raising awareness about the benefits of AI and engaging with local communities to address cultural barriers to adoption.

A study by Nalubega et al. (2018) in Uganda employed a qualitative research design to examine cultural factors affecting AI adoption in the pharmaceutical sector. The study identified a lack of trust in AI technologies due to cultural beliefs and perceptions. The researchers suggested incorporating local values and practices into AI implementation strategies to increase acceptance and adoption in Ugandan pharmaceutical companies.

Cultural barriers to AI adoption in the pharmaceutical business were investigated in a Zambian study by Mwansa et al. (2019) using a mixed-methods methodology. In order to remove cultural obstacles to the application of AI, the study emphasized the value of community involvement and teamwork. To guarantee that AI projects are applicable and accepted in the Zambian setting, the researchers advised include local stakeholders in their conception and execution.

2.4.2.5 Financial constraints

Smith et al. (2018) investigated the relationship between budgetary restrictions and AI adoption in the pharmaceutical business through a quantitative methodology in a study conducted in Germany. The study found that companies with limited financial resources were less likely to invest in AI technologies due to the high costs associated with implementation. The results suggested that overcoming financial constraints is crucial for maximizing the benefits of AI in the pharmaceutical sector. The study recommended that policymakers should provide financial incentives to encourage companies to adopt AI technologies and enhance their competitiveness in the global market.

A mixed-methods technique was used in a Chinese study by Liu et al. (2019) to investigate the influence of budgetary limitations on AI adoption in the pharmaceutical business. According to the study, financially troubled businesses were less likely to invest in AI technology, which decreased their level of innovation and competitiveness. The findings demonstrated the significance of resolving financial obstacles in order to encourage AI adoption in the pharmaceutical industry. According to the report, in order for businesses to obtain AI solutions, they should look for outside funding sources or collaborate with IT companies.

Adekunle et al. (2020) did a study in Nigeria using a qualitative methodology to investigate the obstacles pharmaceutical companies experience while implementing AI technologies. The study discovered that businesses' inability to set aside funds for technological investment posed a significant obstacle to the adoption of AI. The findings highlighted the necessity of government assistance in order to finance and incentivize businesses to invest in artificial intelligence technologies. The study suggested that by providing tax incentives and subsidies to pharmaceutical businesses, politicians might foster an atmosphere that is favourable to the adoption of AI.

In Rwanda, a study by Mutabazi et al. (2017) used a case study methodology to examine the financial implications of AI adoption in the pharmaceutical industry. The study found that companies with limited financial resources were unable to afford the high costs of AI technologies, leading to a lack of technological advancement in the sector. The results suggested that financial constraints hindered the competitiveness of pharmaceutical companies in the global market. The study recommended that companies should explore alternative funding sources such as venture capital or crowdfunding to finance AI projects.

2.5 Conceptual Framework

The outlined research objectives and the interactions between important factors form the basis of the conceptual framework for the study on the difficulties in implementing artificial intelligence (AI) in Zimbabwe's pharmaceutical manufacturing sector. The three primary parts of the framework are the following: the status of AI adoption, obstacles, and the impact of AI on the pharmaceutical manufacturing sector.

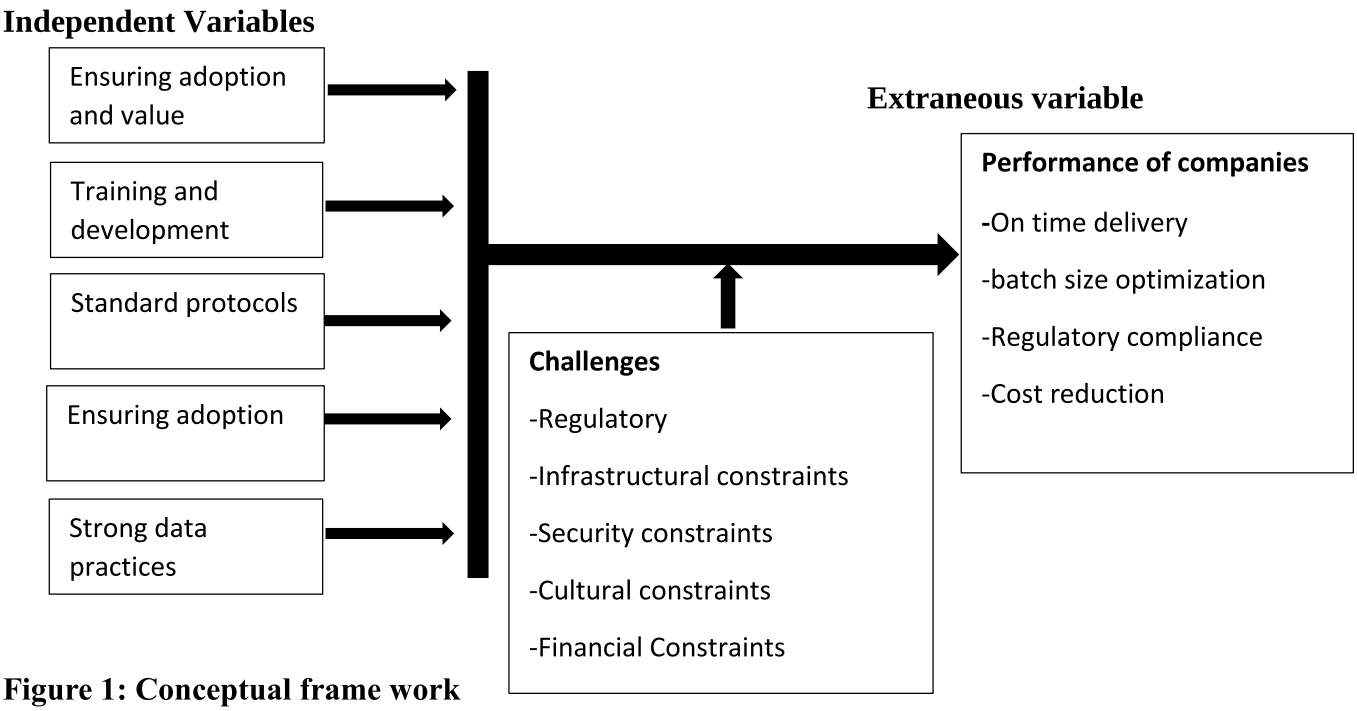

Figure 1: Conceptual frame work

Source: Smith, C., & Johnson, B. (2023)

2.6 Summary

In conclusion, this chapter has shed light on the challenges encountered in the adoption of AI in the manufacturing industry. The review encompassed a conceptual framework, theoretical framework, and empirical studies. The empirical studies highlighted that manufacturing firms in different countries face challenges such as regulatory constraints, financial constraints, security constraints, and infrastructural constraints when it comes to AI adoption. This suggests that these challenges may not be unique to Zimbabwe but are prevalent across various contexts. Furthermore, the literature study showed that adoption rates of AI differ amongst nations, suggesting that institutional backing and the state of technological advancement may have an impact on adoption trends. Overall, this literature analysis serves as a basis for the following chapters of this study and allows for more investigation of the prospects and difficulties related to AI adoption in Zimbabwe's pharmaceutical manufacturing sector. The study techniques to be used to gauge artificial intelligence adoption in Zimbabwe's pharmaceutical manufacturing sector will be the subject of the upcoming chapter which will focus on the methodology of the study, target population and sampling strategy.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the study techniques used to look at obstacles to artificial intelligence adoption in Zimbabwe's pharmaceutical manufacturing sector. This chapter covers a number of research process activities, such as developing a research design, determining the target population and sampling plan, choosing and implementing data collection techniques, using data analysis tools, and taking ethical considerations into account. In order to accomplish the objectives of the study and resolve the research problem, the researcher uses methodology to design and construct the research framework (Kivunja and Kuyini, 2017). The primary aim of this chapter is to elucidate the manner in which the research objectives and questions were effectively tackled, while also providing a rationale for the selection of appropriate methods and procedures.

3.2 Research philosophy

The researcher chose to adopt a pragmatic philosophy for this study since it provides the study with the flexibility to utilize both qualitative and quantitative data in order to effectively solve the research challenge. Pragmatism is a philosophical framework that centres on the pragmatic outcomes of acts and the utility of information. Pragmatism is characterized by its lack of adherence to a singular paradigm or worldview (qualitative or quantitative), instead it embraces the acceptance of diverse perspectives and methodologies as both valid and complementary (Creswell & Clark, 2018). Through the application of a pragmatist mind-set, the research endeavour to successfully integrate the respective merits of qualitative and quantitative data, encompassing comprehensive and vivid descriptions, contextual comprehension, rigorous regression analysis, and the potential for generalizability. The study also adopted a pragmatic approach, drawing inspiration from prior research conducted in related domains. Notable examples of such studies are (Abed et al, 2020) and (Ahmad, 2017).

3.3 Research Approach

The research methodology employed in the study is based on the pragmatic philosophy, which allowed for the integration of both qualitative and quantitative research techniques. Pragmatism in research emphasizes practicality, applicability, and the application of knowledge to real-world circumstances (Davison, 2019). This philosophical approach emphasizes the practical outcomes of ideas and acts above rigid adherence to theoretical frameworks. Pragmatism acknowledges that knowledge is reliant on the context and that the significance of knowledge is in its capacity to address issues and enhance results.

Research using a pragmatic approach focuses on conducting studies with practical consequences that may be implemented to address real-world issues. This technique emphasizes on mixed methods, which include integrating qualitative and quantitative data to get a thorough comprehension of a study subject (Smith and Noble, 2014). It highlights the need of engaging stakeholders and implementing study results in real-world situations. Research generally employs a pragmatic approach that is characterized by flexibility and iteration. Researchers using this method concentrate on formulating research inquiries that tackle tangible problems and creating studies that may provide real insights. They prioritize the fusion of theory and practice, understanding that theory should guide practice, and practice should influence theory. The pragmatic approach in research aims to connect theory with practice, prioritize practical results, and emphasize utilizing research to solve real-world issues. It pushes researchers to contemplate the consequences of their work and interact with stakeholders to guarantee that study results are relevant and beneficial in real-world situations (Davison, 2019).

The qualitative aspect of the research will entail the implementation of interviews with key players within the pharmaceutical manufacturing industry in Zimbabwe. In contrast, the quantitative aspect of the study will involve the implementation of a survey among the firms in Harare and Bulawyo. This survey will employ a structured questionnaire to collect data pertaining to AI technology adoption as a strategy for enhancing pharmaceutical manufacturing industry performance. The data gathered will undergo analysis utilizing descriptive and statistical methods. Through the utilization of this particular research methodology, the study endeavours to provide a thorough and all-encompassing comprehension of the research questions, while simultaneously attending to the research objectives and hypothesis.

3.4 Research Design

The utilization of a descriptive research design is deemed appropriate for this study as it enables the researcher to elucidate and depict the present state of the phenomena being examined. The utilization of a descriptive research design facilitates the researcher in gathering both quantitative and qualitative data from many sources, including surveys and questionnaires.

This research has utilized a case study methodology to examine adoption of AI using Harare and Bulawayo as a case study. Choosing a case study methodology enables a focused inquiry and a thorough examination of the topic. The researcher can look into how the performance of the pharmaceutical manufacturing industry is affected by the use of AI technology and the difficulties associated with it by using a case study technique. A case study is a research method that, according to Prion & Adamson (2007), entails the empirical investigation of a contemporary occurrence in its real-world setting, especially in situations when it is difficult to distinguish the phenomenon from its context.

3.5 Research type

The research type used in this study will be exploratory. A research methodology known as exploratory research seeks to conduct an initial, open-ended investigation of a topic or issue. When there is little prior knowledge or comprehension of a given subject, it is frequently utilized. The first study done to characterize and clarify the nature of a problem is referred to as exploratory research, according to Creswell (2013). The main objectives are to enhance comprehension of the research subject and recognize significant factors, connections, and ideas that could be pertinent. Comparably, Zikmund et al. (2013) define exploratory research as study done to learn new things, generate fresh perspectives, and deepen comprehension of phenomena.

An exploratory research strategy is appropriate for this study for a number of reasons. First off, there isn't much previous study done on this particular subject in relation to Zimbabwe. Moyo et al.'s study from 2022 looked into the obstacles to AI and machine learning adoption in Zimbabwe's insurance sector. Thus, in order to obtain basic data and provide the groundwork for upcoming research, an exploratory strategy would be suitable.

Secondly, technology adoption is a complex and dynamic concept influenced by various internal and external factors. An exploratory research type allows for a comprehensive examination of these factors and their interactions within the context of pharmaceutical manufacturing industry in Zimbabwe. Furthermore, exploratory research is valuable for generating hypotheses and research questions. By conducting exploratory research in this study, the researcher can identify potential effects of technology adoption on performance of pharmaceutical manufacturing industry in Zimbabwe.

Lastly, an exploratory research type provides practical insights and implications for real-world decision-making. By exploring the challenges in the adoption of Artificial intelligence in the in the pharmaceutical manufacturing industry in Zimbabwe, the study can generate valuable information for the pharmaceutical industry in Zimbabwe and beyond, helping them understand the role played by technology adoption in fostering the performance of the pharmaceutical manufacturing industry.

3.6 Research Strategy

The general plan or method utilized to carry out a research study is referred to as the research strategy (Adeel et al, 2018). It describes the procedures and methods that will be used to gather information, analyse it, and come up with answers to research questions or test theories. Depending on the goals of the study and the nature of the research issue, several research methodologies may be used. This study used a survey research strategy based on its research goals. A survey strategy is a research methodology that employs questionnaires or interviews to gather information from a sample of people or organizations. Surveys are typically used to gather data on people's opinions, attitudes, behaviours, or characteristics. According to Bajoren and Bevan (2020), a survey strategy is a research strategy that gathers data from respondents through questionnaires or interviews.

In the context challenges in the adoption of Artificial intelligence in the in the pharmaceutical manufacturing industry in Zimbabwe, a survey strategy is justified for several reasons. Firstly, a survey allows for the collection of data from a large number of respondents, which enhances the generalizability of the findings. By surveying a representative sample of pharmaceutical players in Harare and Bulawayo, the researcher can obtain a broader understanding of the impact of AI adoption and challenges of AI technology adoption.

Secondly, a survey strategy enables the measurement of both objective and subjective information related to pharmaceutical industry performance. Objective data such as financial performance indicators and productivity measures can be collected, as well as subjective data such as perceptions and opinions of managers and employees. This comprehensive data collection approach can provide a more robust analysis of the relationship among the study variables.

Furthermore, a survey strategy allows for the efficient collection of data from geographically dispersed locations. Harare and Bulawayo are very big towns and conducting a survey enabled the researcher to collect data from various pharmaceutical firms located in various corners of the cities. This saves time and resources, making the survey strategy a practical choice for this study.

Moreover, a survey strategy facilitates data standardization and comparability. By using structured questionnaires with predefined response options, researchers can ensure consistency in data collection and minimize potential bias or variations in data interpretation. This enhances the reliability and validity of the study findings. A study conducted by Azudin and Mansor et al. (2018) employed a survey strategy to investigate the adoption ICT practices on the performance of pharmaceutical firms in Japan focusing on Tokyo.

3.7 Time Horizons

The duration of data collection or analysis in a research study is referred to as the time horizon (Field, 2014). It establishes the period for making observations and taking measurements as well as the temporal scope of the investigation. The goals of the study and the characteristics of the phenomenon being studied can influence the time horizons of different research designs.

In this study, a cross-sectional survey was used. One type of research design that gathers data from a sample of participants at one particular moment is the survey cross-sectional study. It seeks to present a moment in time of a specific demographic or occurrence. A cross-sectional study, according to Chirazeni (2018), is "a type of observational study that examines data collected at a single point in time." It enables researchers to compile data on relevant factors and examine their correlations over a predetermined period of time. A survey cross-sectional study could be appropriate in this situation for a number of reasons.

Firstly, this approach allows for the collection of data on AI adoption and the performance of pharmaceutical firms in Harare and Bulawayo at a specific moment. By surveying a representative sample of pharmaceutical firms within a defined timeframe, the researcher could obtain a snapshot of the current state of pharmaceutical industry in Zimbabwe.

Secondly, a survey cross-sectional study enables comparisons between different pharmaceutical firms and locations within the same timeframe. The researcher can investigate variations AI technology adoption, challenges and their effect on the performance of pharmaceutical firms, providing insights into potential differences or similarities between among these firms. This comparison analysis can help us comprehend the difficulties and impacts of using AI technology on pharmaceutical companies' performance. Azudin and Mansor's (2018) study, which focused on Tokyo and using a survey cross-sectional design, examined the difficulties and outcomes of implementing ICT practices in Japanese pharmaceutical companies, highlighting the usefulness of this strategy for obtaining a momentary representation of the phenomenon of interest.

Furthermore, a survey cross-sectional study allows for efficient data collection and analysis within a specific timeframe. Given the time and resource constraints of the study, collecting data at a single point in time is practical and can provide valuable insights into the challenges of AI adoption. This approach also enables timely decision-making and policy formulation by industry stakeholders.

3.8 Study Area

The area of study in research refers to the specific geographic, organizational, or conceptual domain within which the research is conducted (Khan et al, 2022). It defines the boundaries and scope of the study, focusing on a particular region, industry, population, or phenomenon. The selection of the area of study is influenced by the research objectives, research questions, and the availability of relevant data or resources.

Harare and Bulawayo, the two big cities in Zimbabwe, were chosen as the area of study to examine challenges in the adoption of Artificial intelligence in the in the pharmaceutical manufacturing industry in Zimbabwe. Firstly, Harare and Bulawayo are the largest major urban centres in Zimbabwe with a significant number of pharmaceutical players. Secondly, they are representative of different regions within Zimbabwe, allowing for a comparative analysis of AI adoption in pharmaceutical industry. This comparison can provide insights into potential variations in factors such as infrastructure development, which may influence the effects of AI adoption in pharmaceutical industry. Harare and Bulawayo have well-developed infrastructure, including transportation networks and communication systems, which facilitate data collection and interaction with different pharmaceutical players in the cities. This accessibility enhances the feasibility and efficiency of the research study.

In addition, by focusing on Harare and Bulawayo, the researcher could target a manageable sample size of pharmaceutical players within a specific geographic area. This allowed for more in-depth data collection, analysis, and interpretation, leading to a comprehensive understanding of the subject matter.

3.9 Study population

According to Khan et al. (2022), the study population in research pertains to the particular group or individuals that are the subject of data collection or to whom the research findings are meant to be applied broadly. It stands in for the broader target group that the researchers hope to investigate and make inferences about. The stakeholders involved in pharmaceutical manufacturing that operate in Harare and Bulawayo make up the study population in this instance. The researchers examined barriers to artificial intelligence adoption in Zimbabwe's pharmaceutical manufacturing business by concentrating on this specific group of companies.

3.10 Target Population

In the context of research, the target population is the particular group or persons to whom the findings are meant to be applied (Khan et al., 2022). It is a representation of the broader interest population that the study sample is taken from. The target population were chosen based on the intended scope of generalization, the research questions, and the study objectives. The target organizations were any representatives from generic manufacturers, Specialty manufacturers, Research and development manufactures and any other nature of pharmaceutical manufacturing companies with operations in Harare and Bulawayo. The purpose of the data collection and analysis of AI technology adoption was this particular set of people working in the pharmaceutical industry.

3.10.1 Sampling

In the context of research, sampling is the process of choosing a subset of people or units to include in a study from a broader population (Liang and Shi, 2022). In order to enable researchers to extrapolate and draw conclusions about the larger population from the data gathered, it entails selecting a representative sample that faithfully reflects the traits and diversity of the target population.

3.10.2 Sampling frame

A sampling frame in research refers to a list or representation of the individuals or units that make up the target population from which a sample is selected (Liang and Shi, 2022). It provides a comprehensive and identifiable source from which potential participants can be drawn. The sampling frame serves as a reference point for selecting a representative sample and ensures that every member of the target population has an equal chance of being included in the sample.

In this study, the sampling frame consisted of any representatives from generic manufacturers, Specialty manufacturers, Research and development manufactures and any other nature of pharmaceutical manufacturing in Harare and Bulawayo. This sampling frame provided the researcher with a clear and identifiable source from which the researcher could select participants for the study.

3.10.3 Sample Size

The Rao soft calculator was used to calculate the study's sample size. Researchers can use the calculator, an online tool, to estimate the right sample size, margin of error, confidence level, and response rate for a specific population. A 5% margin of error, a 95% confidence level, and a 50% response rate were established. The Rao soft calculator produced a sample size of 169 based on these inputs.

Table 3.1: Sample size

RESPONDENTS CATEGORY	POPULATION	SAMPLE SIZE
Generic manufacturers	100	50
Specialty manufacturers	40	16
Contract manufactures	60	35
Research and development manufacturers	50	34
Others	50	34
TOTAL	**300**	**169**

3.10.4 Sampling techniques

According to Kothari (2009) sampling technique is the procedure adopted by the researcher in selection of units for the study sample. This study used census.

3.10.4.1 Census sampling

The census procedure entails the examination of the whole population (Pandey, 2015). Data is gathered for every individual unit in the population. The researcher used this sample methodology to collect data from pharmaceutical firms. This sampling method was deemed appropriate because, as stated by Kumar (2015), it is very advantageous when one has to pick a certain number of individuals who are in certain positions to give the necessary information for describing a phenomenon in research. This approach also yields more precise data, since it includes all units without exception (Pandey, 2015).

According to Patton (2015), selecting the most exemplary units from the target population is essential to obtaining the most accurate data. The cases that are selected for study have a direct impact on the research findings. In order to successfully address the research goal and issues, this sample strategy entails carefully picking examples that are rich in information (Leavy, 2017). Therefore, the goal of choosing obstacles to artificial intelligence adoption in Zimbabwean pharmaceutical manufacturing industry firms using Harare and Bulawayo as a case study was to collect information from respondents who have exposure to, experience with, and knowledge of adopting AI technology.

3.11 Data collection

Data collection, according to Kumar (2011), is a strategy used to compile details on a circumstance, issue, or occurrence. Data can be divided into two categories: primary data and secondary data, based on general information gathering techniques.

3.11.1 Primary data

Primary data are those that are gathered newly and for the first time, as per Wallimann (2011), and as such have an original character. It is gathered using questionnaires, interviews, and other techniques. Primary data for this study were gathered from the targeted groups using in-depth interviews and questionnaires.

3.11.1.1 Questionnaires

According to Burke and Christensen (2012), a questionnaire is a self-report data collection tool that research participants complete for the study. Questionnaires were emailed and handed by hand to the respondents in order to gather data. There were three sections on the questionnaire. The first portion contained general information about the organization, including the nature of the organisation, number of years in business and size of the organisation. The second portion measured the level of AI adoption by Zimbabwean pharmaceutical manufacturing companies. The third section contains the possible challenges affecting pharmaceutical companies in the adoption of AI technologies.

A 5-point Likert scale with the following measurements was given to respondents to score their adoption of AI: strongly disagree (1), disagree (2), neutral (3), agree (4), and highly agree (5). Regression analysis was then performed on the data using the information gathered from these measurements. Data on the obstacles to pharmaceutical companies' adoption of AI technology were gathered for the third portion. On a 5-point Likert scale with strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5) as the possible outcomes, respondents were asked to list the major obstacles to the adoption of AI technology.

The questionnaire included both open-ended and closed-ended questions to minimize respondent bias. Whereas closed-ended questions forced respondents to choose from a predetermined list of answers, open-ended questions promoted freedom of speech and allowed respondents to qualify their answers (Walliman, 2011). The utilization of questionnaire-based research was selected due to its capacity to access a wide range of sources and its cost and time-effectiveness (Fellows & Liu, 2009).

3.11.2 Secondary data.

According to Kothari (2004), secondary data are already available, meaning they have previously been gathered and examined by another party. Only publicly available information from pharmaceutical companies' financial filings was used in this study. A number of financial statements, including the cash flow, balance sheet, and income statement, were mentioned.

3.12 Data processing.

Compiling and arranging questionnaire raw data was the first step in the data processing process (Yin, 2014). Kumar (2011) emphasized that the researcher made sure the data is clean, meaning it is devoid of errors and incompleteness. This was accomplished by carefully editing and reviewing the finished research instruments to find and reduce as much as possible errors, incompleteness, incorrect categorization, and gaps in the data collected from the respondents. One respondent at a time, all of their answers to all of the questions were looked through to get a complete picture of the responses, which also aided in evaluating their internal consistency.

Following data cleaning, each variable's measurement method from the study equipment was used to code the data. In order to identify the many types of data scales that needed to be handled, coding was done. It was crucial to define these data scales since the scale of the data influences the choice of statistical test to apply. Discrete variables, or completely distinct categories of data, such as demographic information like respondents' age group, gender, and firm category, were simply indicated by the nominal scale.

The ordinal scales classified and introduced an order into the data. This encompassed rating scales and Likert scales where, for example, ‘Very significant ’is stronger than ‘of little significant’. The Statistical Package for Social Scientist (SPSS) version 22 and EViews 10 were used for computing the collected data on the effects of technology on performance of pharmaceutical firms as well as generating a data base of responses.

3.12.1 Reliability and normality test of data

Before undertaking statistical tests, the researcher determined whether the data was obtained through a normal population. *Gupta et al*. (2019) emphasized that an assessment of the normality of data is a prerequisite for statistical tests as Statistical tests have the advantage of making an objective judgment of normality.

Since the one of the analysis techniques was regression, to test normality of data, the Jarque-Bera approach was used to test normality. This procedure posits that the probability value of Jarque should be above 0.05 if normality is present. This was conducted using EViews 10. Blanchard (2020) argues that the method is suitable for sample sizes between 30 and 200. Since this study's sample fell within this range, the research adopted this approach.

3.13 Data presentation and analysis

The Statistical Package for Social Scientist (SPSS) version 22 and EViews 10 were used for computing the collected data on the challenges in the adoption of Artificial intelligence in the in the pharmaceutical manufacturing industry in Zimbabwe as well as generating a data base of responses. The justification for the two soft wares is that the former is powerful tool for analysing data using descriptive statistics while EViews 10 is a powerful tool for analysing data using regression analysis as it can give estimates of R^2, adjusted R^2, Durbin Watson statistic, F-Statistic value and its probability. All these parameters are deemed as important aspects to be considered in the robustness of regression results (Gujarati, 2004).

3.13.1 Analysis of respondent's profile

The respondent's profile was analysed using descriptive statistics in the form of frequencies and percentages generated. The data gathered and analysed against demographic variables using inferential statistics. Frequency statistics simply counted the number of times that in each respondents' profile variable occurred. Frequency analysis is an important area of statistics in this research that deal with the number of occurrences and percentage (Gupta *et al.*; 2019).

A 5-point Likert scale was used to measure the intensity of respondent's feelings concerning the statements in the Likert-scale. The measurements were used to analyse and rank the challenges to the implementation of AI adoption. Dawson (2019) supports the use of Likert-scale rankings as they are effective where numbers can be used to quantify the results of measuring attitudes, preferences, and perceptions.

3.14 Data Analysis techniques.

The following data analysis techniques as outlined in the table above was used to analyse data.

3.14.1 Frequency distribution and percentages.

In order to analyse the first component of the responses, which included the respondents' backgrounds, descriptive statistics in the form of frequencies and percentages were used. According to Hamid and Chin (2015), a set of selection's frequencies were obtained using the frequencies statistic. A five-point grading system was employed, with 1 denoting never, 2 occasionally, 3 frequently, 4 very frequently, and 5 always. The frequency levels were classified using the following rating measures. Zero ≤ "not frequent," one ≤ "slightly frequent," two ≤ "somewhat frequent," three ≤ "frequent," four ≤ "very frequent," and five ≤ "very frequent." A selection that is most frequently chosen indicates that respondents find it to be their favourite. Pie charts and bar charts were created using the outcome data to aid with comprehension.

3.14.2 Regression analysis.

Using the Ordinary Least (OLS) approach the study will run regression to ascertain the challenges influencing AI adoption. The model is specified below.

$\text{Adop} = \beta_0 + \beta_1\text{Reg} + \beta_2\text{Infr} + \beta_3\text{Fin} + \beta_4\text{Sec} + \beta_5\text{Cul} + \varepsilon$

$Where:$

$Adop\text{: } AI\ Technology\ adoption.$

$Reg\text{: } Regulatory\ constraints.$

$Infr\text{: } Infrastructure\ constraints$

$Fin\text{: } Financial\ constraints$

$Sec\text{: } Security\ constraints$

$Cul\text{: } Cultural\ constraints$

$\beta_0\text{: } intercept.$

$\beta_{1,}\beta_2, \beta_3, \beta_{4,}, \beta_{5,}\text{: } Structural\ parameter\ coefficients.$

$\varepsilon\text{: } Error\ term.$

3.15 Data Validity and Reliability

3.15.1 Data Validity

Dawson (2019) defines validity as degree to which the researcher has measured what he set out to measure. To ensure validity of data the following are going to be carried out:

A questionnaire was pretested on small number of people in selected pharmaceutical stakeholders using Pilot study before it was used in the whole city. Responses were then assessed to determine whether they provided the actual information as anticipated. The results were used to improve the research instrument.

3.15.2 Reliability

According to Campbell et al. (2013), in order for other researchers to be able to duplicate the study, dependability is crucial for demonstrating dependability by offering detailed explanations of the design elements and procedures. Therefore, accurate documentation of the research procedures was necessary to attain reliability in this study. According to Frels and Onwuegbuzie (2013), employing a suitable research methodology ensures the gathering of dependable data and the capacity to derive dependable findings. Additionally, a Cronbach α minimum value 0.8 was considered acceptable as indicating internal reliability of the questionnaire. The Cronbach α formula is given by:

$$\boldsymbol{\alpha}= \frac{\boldsymbol{k}}{\boldsymbol{k-1}}\left[\frac{\sum_{i=1}^{k} \boldsymbol{Pi(1-Pi)}}{\delta_{x}^{2}}\right]$$

Where

α =Cronbach s coefficient

k= number of items

Pi=Proportion of the respondents answering a research question in a certain way.

The research tools were also subjected to peer review to ensure its validity. As stated by Creswell (2017), the researcher asked participants in the study to check the accuracy of the account for example asking if the description is complete and realistic and if themes are accurate. The researcher also made sure that informants were very clear on the nature of the research for example why research is there, what is being studied and how data will be collected and how is going to be used.

3.16 Ethical Considerations

The study aims to investigate technology challenges in the adoption of Artificial intelligence in the in the pharmaceutical manufacturing industry in Zimbabwe. The study involved collecting data from pharmaceutical players using surveys, interviews, and questionnaires. The study adhered to the following ethical principles:

3.16.1 Seeking approval from research supervisor and the University

According to Cresswell (2017), it is upon all researchers at the university to familiarize themselves and adhere to the ethical code of the institution. The researcher therefore adhered to the ethical code of the Bindura University of Science Education. Before going to the industry to collect data, the researcher consulted the supervisor who gave the permission to the researcher to conduct the study. The researcher also submitted a letter to the Department for requesting permission to conduct a study. Having gotten the Institutional and research supervisors', approval the researcher proceeded with the study and went to the industry to collect data.

3.16.2 Respect for autonomy

The research upheld the participants' rights and dignity while making sure they were fully informed about the goals, procedures, and advantages of the study. Before any data was collected, all participants gave their informed consent, and they were free to leave the study at any moment without incurring any fees or being under any kind of duress.

3.16.3 Beneficence

The goal of the study was to reduce research-related risks and increase benefits for both individuals and society as a whole. The study ensured that the participants were not subjected to any physical, psychological, social, or financial harm prior to, during, or following the study period, and safeguarded their confidentiality, identity, and data.

3.16.4 Justice

The study ensured that the participants were treated fairly and equitably and that they were not exploited or discriminated against them based on their age, gender, race, ethnicity, religion, or any other factor.

3.16.5 Dissemination of information

The researcher will send a hard copy of this dissertation to the Department where the study will be conducted, and the researcher's University.

3.16.6 Data disposal

A suitable time will be decided for disposing of the records at the end of the research project. Disposal of records will be done by removing all labels and titles that could lead to identification and all documents will be shred.

3.17 Conclusion

This chapter provides a comprehensive overview of key aspects of research design, research paradigm, data collection methods, sampling methods, and other important considerations in the research process. It explores the importance of selecting an appropriate research design based on the research questions and objectives, and how it should align with the chosen research paradigm. Various data collection methods, such as interviews, surveys, questionnaires, and document analysis, are discussed in relation to their suitability for this research context. The chapter also covers sampling methods, including probability and non-probability sampling, and emphasizes the significance of selecting a representative sample. Other aspects, such as ethical considerations, data analysis techniques, and validity and reliability, are examined to ensure the trustworthiness and quality of research findings. Overall, this chapter provides researchers with a comprehensive understanding of these essential aspects and their interconnections, guiding them towards conducting robust and rigorous research studies. The next chapter will focus on data presentation processes which will involve scanning and sifting the collected data, organizing it and summarizing it as well as interpreting research findings.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter presents the key findings from the data collected during the research study on the challenges to adopting artificial intelligence (AI) technologies in Zimbabwe's pharmaceutical manufacturing industry. The analysis examines the major barriers, opportunities, and considerations that industry leaders and experts identified through the survey process. Particular attention is paid to factors such as technological infrastructure, workforce skills, regulatory environment, and organizational readiness. Additionally, the chapter explores the potential benefits and risks of AI adoption that emerged from the study, as well as the strategies and best practices recommended by participants for overcoming the challenges. The presentation of results aims to provide a comprehensive and data-driven assessment to guide policymakers, industry stakeholders, and technology providers on the path forward for increasing AI utilization in this critical sector of Zimbabwe's economy.

4.2 General responses

4.2.1 Response rate

The first set of results to be presented is the survey response rate. Out of the 169 questionnaires distributed both online and physically to pharmaceutical companies such as Varichem, Datlabs, CAPS, Pharmanova, Cosmpharm, PlusFive, Chemplex and SAAPS, 130 were returned, translating to an overall response rate of 77%. This response rate is well within the 60-80% range that Fan et al. (2021) argue is sufficient to make meaningful deductions from research results. The high level of participation suggests the topic holds significant relevance and interest for industry stakeholders in Zimbabwe's pharmaceutical manufacturing sector, providing confidence in the representativeness of the data collected. With this strong response rate established, the chapter will now delve into the key findings and insights uncovered through the analysis of the survey and interview data.

4.2.2 Nature of pharmaceutical manufacturing company

Nature of pharmaceutical company	Response Rate
Research and development	19%
Contract manufacturing	21%
Generic manufacturing	34%
Specialty manufacturing	9%
Others	17%

Table 4.1 Nature of pharmaceutical manufacturing company

Source: Primary data computations

The survey respondent data shows a diverse representation across nature or type of manufacturing company within Zimbabwe's pharmaceutical manufacturing sector. The largest segment was the generic manufacturing range, accounting for 34% of participants. This was followed by contract manufacturing group at 21%, research and development group at 19%, the Others group at 17% and lastly the specialty pharmaceutical manufacturing group at 9% respectively. This balanced distribution across the nature of pharmaceutical companies provides valuable insights into the perspectives and concerns around AI adoption from both seasoned industry veterans and newer entrants. The range of type of manufacturing companies represented enhances the credibility of the findings and ensures they reflect the views of the broader pharmaceutical nature in Zimbabwe, rather than being skewed towards any one type of manufacturing group.

4.2.3 Organization size

The figure below shows the results on the Organization size

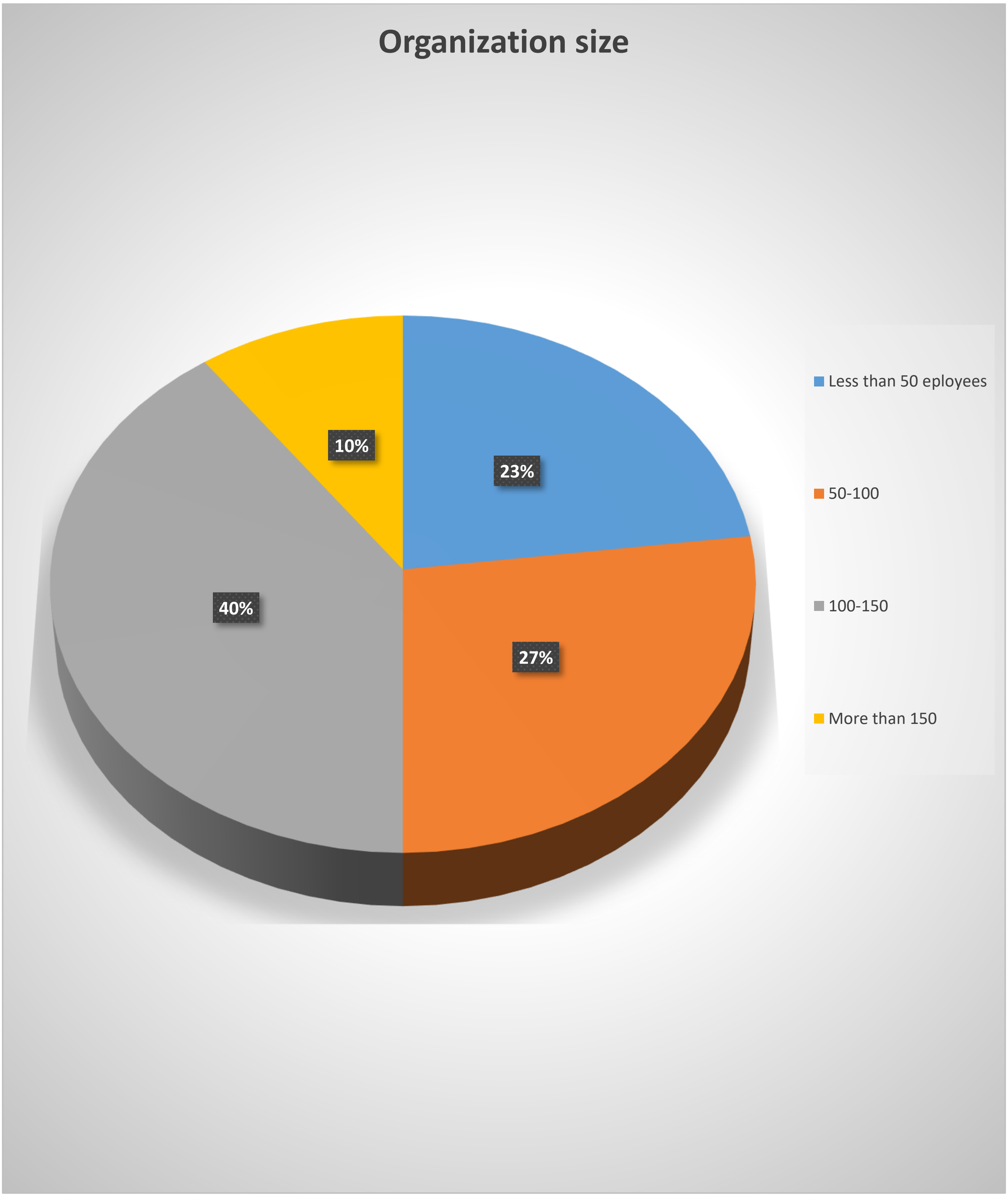

Figure 4.2: Organization size

Source: Primary data computations

The analysis of the respondents' Organization size reveals a highly represented pool of participants. The largest group, comprising 40% of the total, held a 100-150 employees. This was followed by those organizations with 50-100 employees, who made up 27% of the sample. Those organizations with less than 50 employees accounted for 23%, while the smallest segment, at 10%, had more than 150 employees.

This distribution of the organization size speaks to the size of pharmaceutical manufacturing companies available in Zimbabwe. The fact that 67% of respondents possessed to have more than 50 employees indicates companies with a fairly large workforce with strong knowledge and likely deep subject matter expertise. The 10% with more than 150 employees further bolsters the credibility of the insights provided, as these organizations would be expected to have the most advanced knowledge and understanding of the industry's challenges and technology trends.

The mix of the organization sizes represented enhances the richness of the data collected. It ensures the perspectives shared encompass both the operational realities on the ground as well as the strategic and innovative thinking at the highest levels of the pharmaceutical sector. This diversity of organization sizes strengthens the reliability of the study's findings and their applicability to driving meaningful change in the adoption of AI technologies within this critical industry.

4.2.4 Number of years in business

It was important to establish the level of experience in business for the organisations. The results are shown in the figure below.

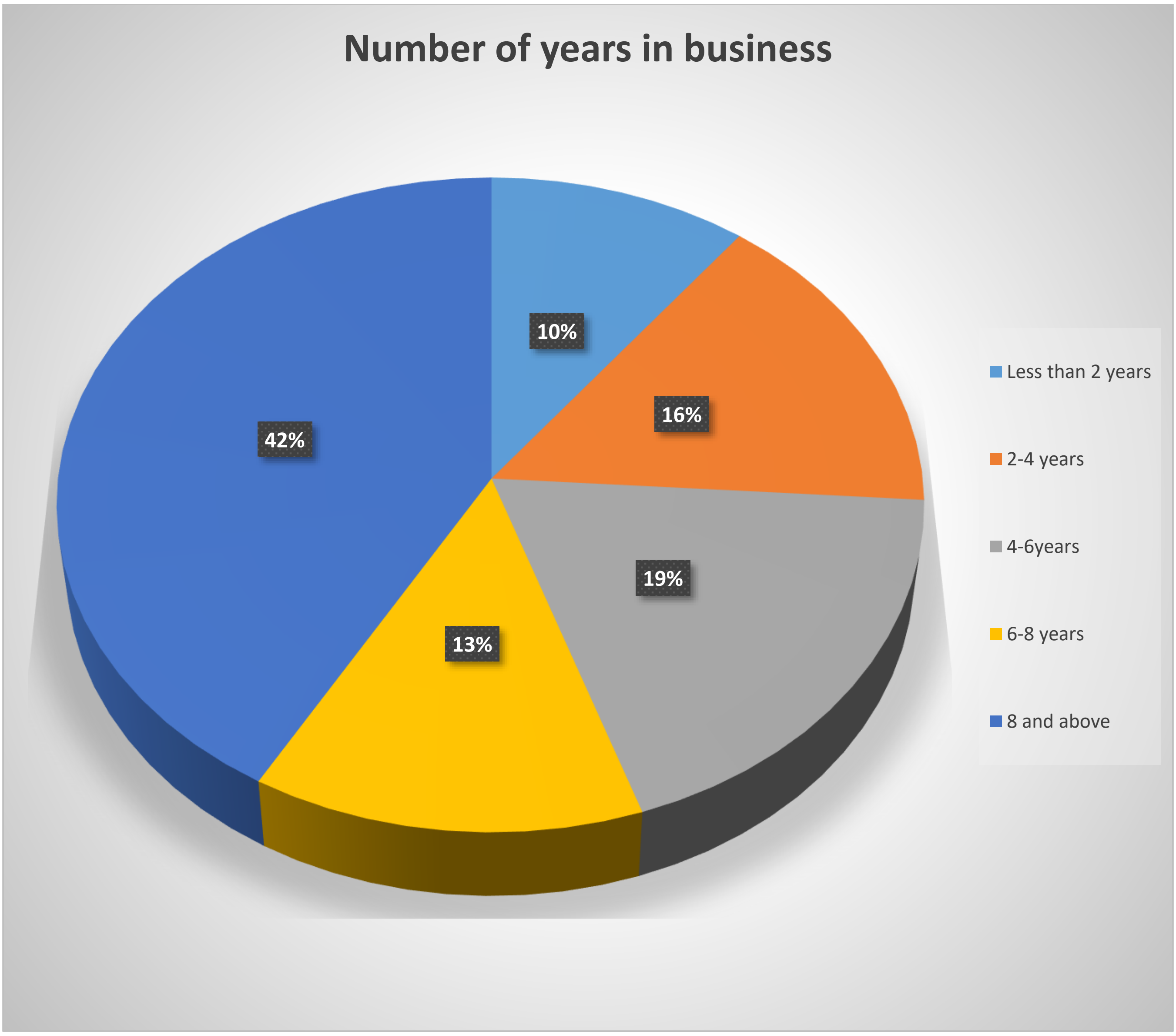

Figure 4.3: Number of years in business

Source: Primary data computations

The analysis of the Organisation industry experience provides valuable insights into the depth of knowledge and perspectives captured in the study. The data shows a well-balanced representation across varying levels of tenure within the pharmaceutical manufacturing sector in Zimbabwe.

The largest group, at 42%, had more than 8 years of experience, followed by those with 4-6 years at 19% and 2-4 years at 16%. This indicates a significant portion of the sample, over

74%, possessed at least four years of hands-on industry knowledge and exposure. The 10% with less than 2 years of experience further bolsters this core group of relatively newer entrants to the field. At the same time, the study also incorporated perspectives from more seasoned organizations, with 42% of the organisations having over eight years of experience. This blend of newer and more experienced voices lends credibility to the findings, as it ensures the challenges, opportunities, and industry dynamics captured reflect both emerging trends and long-standing realities. This range in tenure levels, from the newest recruits to the veteran leaders, enhances the comprehensiveness of the data and strengthens the ability to draw meaningful conclusions about the complex realities of AI adoption in this industry.

4.3 Level of the adoption of AI in the pharmaceutical manufacturing industry in Zimbabwe.

4.3.1 Perceived Compatibility

Qn/No	Statement	Number	Classification	Percent
1	AI technologies are compatible with the current industrial systems.	130	Strongly agree	36.59
			Agree	36.59
			Neutral	12.20
			Disagree	12.20
			Strongly Disagree	2.44
2	AI technologies are compatible with the supply chain styles and strategies	130	Strongly agree	48.78
			Agree	24.39
			Neutral	12.20
			Disagree	9.76
			Strongly Disagree	4.88
3	AI technology is not consistent with the current supply chain platforms.	130	Strongly agree	60.98
			Agree	24.39
			Neutral	9.76
			Disagree	3.66
			Strongly Disagree	1.22

Table 4.2: Perceived compatibility

Source: Primary data computations

The survey results regarding the perceived compatibility of AI technologies with the current industrial systems in Zimbabwe's pharmaceutical manufacturing industry reveal a predominantly positive sentiment, with 73.18% of respondents either strongly agreeing (36.59%) or agreeing (36.59%) that AI is compatible with existing frameworks and infrastructure. However, the findings also uncover a minority of respondents who expressed reservations, with 12.20% remaining neutral and an additional 12.20% and 2.44% disagreeing and strongly disagreeing, respectively. This diversity of perspectives highlights the need for industry leaders to address any lingering concerns or barriers through targeted strategies, such as educational campaigns and pilot projects, in order to foster a more unified, AI-ready mind-set across the pharmaceutical manufacturing landscape in Zimbabwe.

The survey results presented in Table 4.2 regarding the perceived compatibility of AI technologies with the supply chain styles and strategies in Zimbabwe's pharmaceutical manufacturing industry reveal a strong positive sentiment. A significant majority of 73.17% of respondents either strongly agreed (48.78%) or agreed (24.39%) that AI can be effectively integrated with the existing supply chain frameworks and approaches. This suggests a high level of optimism among industry stakeholders about the potential for AI to enhance and streamline supply chain operations, improving efficiency, visibility, and responsiveness. However, the findings also uncover a minority of respondents who expressed reservations, with 12.20% remaining neutral and an additional 9.76% and 4.88% disagreeing and strongly disagreeing, respectively. This diversity of perspectives underscores the need for industry leaders to address any lingering concerns through targeted initiatives that demonstrate the tangible benefits of AI-powered supply chain solutions, in order to build a more unified and enthusiastic acceptance of these advanced technologies across the pharmaceutical manufacturing landscape in Zimbabwe.

The survey results presented in Table 4.2 reveal a strong perception among respondents that AI technology is not consistent with the current supply chain platforms in Zimbabwe's pharmaceutical manufacturing industry. A substantial majority of 85.37% either strongly agreed (60.98%) or agreed (24.39%) with this assertion, indicating a widespread belief that the integration of AI would face significant compatibility challenges with the existing supply chain infrastructure and systems. This suggests that industry stakeholders may perceive AI as disruptive to the established supply chain operations, potentially requiring extensive reconfiguration and modernization efforts to achieve seamless integration. The findings also show a smaller proportion of respondents who remained neutral (9.76%) or disagreed (3.66%

disagreed, 1.22% strongly disagreed) with the incompatibility of AI, reflecting a diversity of perspectives within the industry. Addressing these concerns and perceptions will be crucial for facilitating the successful adoption and implementation of AI-powered supply chain solutions in the pharmaceutical sector in Zimbabwe.

4.3.2 Trialability

Qn/No	Statement	Number	Classification	Percent
1	AI technology provides chances for future usages	130	Strongly agree	36.59
			Agree	36.59
			Neutral	12.20
			Disagree	12.20
			Strongly Disagree	2.44
2	AI technology helps in assessing future supply chain tasks	130	Strongly agree	48.78
			Agree	24.39
			Neutral	12.20
			Disagree	9.76
			Strongly Disagree	4.88
3	AI is innovative because it provides chances to have rich content in supply chain content in supply chain settings.	130	Strongly agree	60.98
			Agree	24.39
			Neutral	9.76
			Disagree	3.66
			Strongly Disagree	1.22

Table 4.3: Trialability

Source: Primary data Computations

The survey results presented in Table 4.3 regarding the Trialability dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a positive perception among respondents about the potential for future usages. A majority of 73.18% either strongly agreed (36.59%) or agreed (36.59%) that AI technology provides opportunities for future utilization and applications. This suggests that industry stakeholders see AI as a versatile and adaptable technology that can be leveraged to address a range of current and emerging needs within the pharmaceutical sector. However, the findings also reveal a minority of respondents who expressed reservations, with

12.20% remaining neutral and an additional 12.20% and 2.44% disagreeing and strongly disagreeing, respectively. This diversity of perspectives underscores the importance of proactively addressing any concerns or uncertainties about the Trialability of AI, so as to foster a more unified and enthusiastic adoption of these advanced technologies across the pharmaceutical manufacturing landscape in Zimbabwe.

The survey results presented in Table 4.3 regarding the Trialability dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a positive perception among respondents about the ability of AI to assist in assessing future supply chain tasks. A significant majority of 73.17% either strongly agreed (48.78%) or agreed (24.39%) that AI technology can help evaluate and plan for upcoming supply chain requirements and challenges. This suggests that industry stakeholders see the potential for AI-powered analytics and decision-support capabilities to enhance supply chain visibility, forecasting, and preparation for future scenarios. However, the findings also reveal a minority of respondents who expressed reservations, with 12.20% remaining neutral and an additional 9.76% and 4.88% disagreeing and strongly disagreeing, respectively. This diversity of perspectives underscores the importance of proactively addressing any concerns or uncertainties about the Trialability and supply chain-related applications of AI, in order to foster a more unified and enthusiastic adoption of these advanced technologies across the pharmaceutical manufacturing landscape in Zimbabwe.

The survey results presented in Table 4.3 regarding the Trialability dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a strong positive perception that AI is innovative due to its potential to provide rich content and capabilities within supply chain settings. A substantial majority of 85.37% of respondents either strongly agreed (60.98%) or agreed (24.39%) with this assertion, suggesting that industry stakeholders see AI as a transformative technology that can significantly enhance the depth and quality of supply chain-related content, data, and insights. This perception likely stems from the advanced analytical, automation, and decision-support capabilities that AI can bring to supply chain management. However, the findings also reveal a minority of respondents who expressed reservations, with 9.76% remaining neutral and an additional 3.66% and 1.22% disagreeing and strongly disagreeing, respectively. Addressing these concerns and further demonstrating the innovative supply chain-related applications of AI will be crucial for driving widespread adoption and integration within the pharmaceutical manufacturing sector in Zimbabwe.

4.3.3 Relative advantage

Qn/No	Statement	Number	Classification	Percent
1	AI technology provides more supply chain features than old ones.	130	Strongly agree	36.59
			Agree	36.59
			Neutral	12.20
			Disagree	12.20
			Strongly Disagree	2.44
2	AI technology helps me to save time and effort, as compared with old systems.	130	Strongly agree	48.78
			Agree	24.39
			Neutral	12.20
			Disagree	9.76
			Strongly Disagree	4.88
3	AI technology is not consistent with the current supply chain platforms.	130	Strongly agree	20.98
			Agree	24.39
			Neutral	29.76
			Disagree	13.66
			Strongly Disagree	11.22

Table 4.4: Relative Advantage of AI

Source: Primary data Computations

The survey results presented in Table 4.4 regarding the Relative Advantage dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a positive perception that AI offers more advanced supply chain features compared to older technologies. A majority of 73.18% of respondents either strongly agreed (36.59%) or agreed (36.59%) with this assertion, suggesting that industry stakeholders see AI as a superior solution that can deliver enhanced capabilities, functionalities, and benefits for supply chain management. This perception likely stems from the data-driven optimization, predictive analytics, and automation capabilities that

AI can provide to improve supply chain visibility, efficiency, and responsiveness. However, the findings also reveal a minority of respondents who were neutral (12.20%) or disagreed (12.20% disagreed, 2.44% strongly disagreed) with the notion that AI technology offers more advanced supply chain features. Addressing these concerns and clearly demonstrating the relative advantages of AI-powered supply chain solutions will be crucial for driving widespread adoption and integration within the pharmaceutical manufacturing sector in Zimbabwe.

The survey results presented in Table 4.4 regarding the Relative Advantage dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a positive perception that AI can help save time and effort compared to older systems. A significant majority of 73.17% of respondents either strongly agreed (48.78%) or agreed (24.39%) with this assertion, suggesting that industry stakeholders see AI as a more efficient and productive solution for supply chain management tasks. This perception likely stems from the automation, optimization, and decision-support capabilities that AI can provide to streamline workflows, reduce manual efforts, and accelerate supply chain processes. However, the findings also reveal a minority of respondents who were neutral (12.20%) or disagreed (9.76% disagreed, 4.88% strongly disagreed) with the notion that AI technology offers time and effort savings over legacy systems. Addressing these concerns and clearly demonstrating the relative advantages of AI-powered supply chain solutions in terms of improved productivity and reduced workloads will be crucial for driving widespread adoption and integration within the pharmaceutical manufacturing sector in Zimbabwe.

The survey results presented in Table 4.4 regarding the Relative Advantage dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a mixed perception about the consistency of AI with current supply chain platforms. While a notable proportion of respondents, 45.37% in total, either strongly agreed (20.98%) or agreed (24.39%) that AI technology is not consistent with existing supply chain systems, a significant number, 29.76%, remained neutral on the matter. Additionally, 24.88% of respondents disagreed (13.66%) or strongly disagreed (11.22%) with the assertion, suggesting that they see AI as being compatible with the current supply chain infrastructure. This diversity of perspectives highlights the need for further exploration and understanding of the integration challenges and requirements between AI-powered solutions and the existing supply chain platforms used in the pharmaceutical industry in Zimbabwe. Addressing any perceived inconsistencies or integration barriers will be crucial for facilitating the widespread adoption and effective implementation of AI technologies across the supply chain operations.

4.3.4 Ease of Doing Business

Qn/No	Statement	Number	Classification	Percent
1	AI technology is preferred by supply chain managers and staff	130	Strongly agree	34.50
			Agree	34.50
			Neutral	13.80
			Disagree	13.20
			Strongly Disagree	3.00
2	AI technology is known by many adopters in our organisation.	130	Strongly agree	48.78
			Agree	24.39
			Neutral	12.20
			Disagree	9.76
			Strongly Disagree	4.88
3	AI technology is widely accepted at the institutional level	130	Strongly agree	60.98
			Agree	24.39
			Neutral	9.76
			Disagree	3.66
			Strongly Disagree	1.22

Table 4.5: Ease of doing business

Source: Primary data Computations

The survey results presented in Table 4.4 regarding the Ease of Doing Business dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a positive perception that AI is preferred by supply chain managers and staff. A majority of 69% of respondents either strongly agreed (34.50%) or agreed (34.50%) with this assertion, suggesting that industry stakeholders see AI as a valuable and desirable solution for supply chain operations. This perception likely stems from the efficiency, productivity, and decision-support capabilities that AI can provide to supply chain professionals, helping them streamline workflows, enhance visibility, and make more informed decisions. However, the findings also reveal a minority of respondents who were neutral (13.80%) or disagreed (13.20% disagreed, 3.00% strongly disagreed) with the notion that AI technology is preferred by supply chain managers and staff. Addressing any concerns or uncertainties about the user-friendliness and acceptance of AI-powered tools will be crucial for ensuring successful adoption and integration within the pharmaceutical supply chain in Zimbabwe.

Additionally, the survey results presented in Table 4.5 regarding the Ease of Doing Business dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a positive perception that AI is widely known and recognized by adopters within the organization. A significant majority of 73.17% of respondents either strongly agreed (48.78%) or agreed (24.39%) that AI technology is known by many adopters in the organization. This suggests that industry stakeholders have a good understanding and awareness of AI capabilities and applications, which is a crucial prerequisite for successful adoption and integration. The high level of familiarity with AI technology among adopter’s likely stems from initiatives to educate and inform supply chain professionals about the benefits and potential of AI-powered solutions. However, the findings also reveal a minority of respondents who were neutral (12.20%) or disagreed (9.76% disagreed, 4.88% strongly disagreed) with the assertion that AI is widely known within the organization. Continuous efforts to enhance awareness and demonstrate the value of AI technology will be important for driving broader acceptance and adoption across the pharmaceutical supply chain in Zimbabwe.

The survey results presented in Table 4.5 regarding the Ease of Doing Business dimension of AI technology in Zimbabwe's pharmaceutical industry indicate a strong perception that AI is widely accepted at the institutional level. A substantial majority of 85.37% of respondents either strongly agreed (60.98%) or agreed (24.39%) that AI technology is widely accepted within the organization. This suggests that there is a high level of institutional support and buy-in for the adoption and integration of AI-powered solutions across the pharmaceutical supply chain. The strong institutional acceptance is likely driven by a recognition of the potential benefits that AI can offer, such as improved efficiency, enhanced decision-making, and increased competitiveness. However, the findings also reveal a small minority of respondents who were neutral (9.76%) or disagreed (3.66% disagreed, 1.22% strongly disagreed) with the assertion of widespread institutional acceptance. Maintaining and further strengthening this high level of acceptance will be crucial for facilitating the successful implementation and scaling of AI technologies within the pharmaceutical industry in Zimbabwe.

4.3.5 Technology Export

Qn/No	Statement	Number	Classification	Percent
1	AI technology innovation features are highly demanded at the institutional level	130	Strongly agree	30.40
			Agree	30.60
			Neutral	15.00
			Disagree	13.56
			Strongly Disagree	10.44
2	IA technology does not satisfy the supply chain staff needs.	130	Strongly agree	48.78
			Agree	20.39
			Neutral	16.20
			Disagree	9.76
			Strongly Disagree	4.88
3	IA technology satisfies the organisation needs; it was invented by other countries.	130	Strongly agree	20.98
			Agree	21.08
			Neutral	40.76
			Disagree	10.66
			Strongly Disagree	7.90

Table 4.6: Technology Export

Source: Primary data Computations

The survey results presented in Table 4.6 regarding the Technology Export AI dimension in Zimbabwe's pharmaceutical industry indicate a relatively positive, but also mixed, perception about the institutional demand for AI technology innovation features. A majority of 61% of respondents either strongly agreed (30.40%) or agreed (30.60%) that AI innovation features are highly demanded at the institutional level. This suggests that there is a recognition and appreciation within the industry for the advanced capabilities and features that AI-powered solutions can provide to enhance supply chain operations and performance. However, the findings also reveal a notable proportion of respondents who were neutral (15.00%) or disagreed (13.56% disagreed, 10.44% strongly disagreed) with the assertion of high institutional demand for AI innovation. This points to the need for continued efforts to educate and demonstrate the specific benefits and value proposition of AI-enabled features to drive stronger institutional-level demand and adoption within the pharmaceutical supply chain in Zimbabwe.

The survey results presented in Table 4.6 regarding the Technology Export AI dimension in Zimbabwe's pharmaceutical industry indicate a significant perception that AI technology does not fully satisfy the needs of supply chain staff. A majority of 69.17% of respondents either strongly agreed (48.78%) or agreed (20.39%) with the assertion that AI technology does not meet the requirements and expectations of supply chain personnel. This suggests that there may be a disconnect between the capabilities and features of the AI solutions being implemented and the actual needs and pain points experienced by the supply chain staff. Potential areas of dissatisfaction could include the user-friendliness, integration, or functionality of the AI-powered tools. However, the findings also reveal a smaller proportion of respondents who were neutral (16.20%) or disagreed (9.76% disagreed, 4.88% strongly disagreed) with the notion that AI technology does not satisfy staff needs. Bridging this gap and ensuring that AI solutions are aligned with the specific requirements and preferences of supply chain professionals will be crucial for driving greater acceptance and effective utilization of the technology within the pharmaceutical industry in Zimbabwe.

The survey results presented in Table 4.6 regarding the Technology Export AI dimension in Zimbabwe's pharmaceutical industry indicate a mixed perception about whether AI technology, which was invented by other countries, satisfies the needs of the organization. While a combined 42.06% of respondents either strongly agreed (20.98%) or agreed (21.08%) with this assertion, a significant proportion of 40.76% remained neutral. This suggests that there is a level of uncertainty or ambiguity among industry stakeholders about the extent to which the AI solutions, which have been developed externally, are meeting the specific requirements and needs of the pharmaceutical organizations in Zimbabwe. The high neutral response rate may reflect a lack of a clear understanding or evidence regarding the alignment between the imported AI technology and the organization's needs. Additionally, the findings reveal that 18.56% of respondents disagreed (10.66%) or strongly disagreed (7.90%) that the AI technology satisfies the organization's needs, indicating that a minority of stakeholders perceive a mismatch between the technology and their operational requirements. Addressing these concerns and ensuring the relevance and effectiveness of AI solutions will be crucial for driving successful adoption and integration within the Zimbabwean pharmaceutical supply chain.

4.3.5 Technology Acceptance rate

Qn/No	Statement	Number	Classification	Percent
1	Institutions are willing to upgrade their supply chain platforms and ready to include AI as part of it.	130	Strongly agree	30.00
			Agree	33.00
			Neutral	15.00
			Disagree	14.03
			Strongly Disagree	7.07
2	Institutions are ready to adopt AI technology for supply chain purposes	130	Strongly agree	48.78
			Agree	24.39
			Neutral	12.20
			Disagree	9.76
			Strongly Disagree	4.88

Table 4.7: Technology Acceptance rate

Source: Primary data Computations

The survey results presented in Table 4.7 regarding the Technology Acceptance Rate of AI in Zimbabwe's pharmaceutical industry indicate a generally positive outlook on the willingness of institutions to upgrade their supply chain platforms and incorporate AI as part of it. A majority of 63% of respondents either strongly agreed (30.00%) or agreed (33.00%) that institutions are ready to include AI as part of their supply chain modernization efforts. This suggests that there is a growing recognition and acceptance among industry stakeholders of the need to adopt and integrate advanced technologies, such as AI, to enhance the efficiency and performance of the pharmaceutical supply chain. The relatively high level of agreement on the institutions' readiness to upgrade their platforms and embrace AI technology indicates a favourable environment for the adoption and implementation of these solutions. However, the findings also reveal a notable proportion of respondents who were neutral (15.00%) or disagreed (14.03% disagreed, 7.07% strongly disagreed) with the assertion, highlighting the need to address any lingering concerns or barriers to AI adoption. Continued efforts to demonstrate the tangible benefits and seamless integration of AI-powered solutions will be crucial for driving broader acceptance and successful implementation within the Zimbabwean pharmaceutical industry.

The survey results presented in Table 4.7 regarding the Technology Acceptance Rate of AI in Zimbabwe's pharmaceutical industry indicate a strong positive sentiment towards the readiness of institutions to adopt AI technology for supply chain purposes. A significant majority of 73.17% of respondents either strongly agreed (48.78%) or agreed (24.39%) that institutions are ready to embrace AI-powered solutions to enhance their supply chain operations. This suggests a high level of institutional willingness and openness to incorporate AI technology as part of their strategic initiatives to improve efficiency, reduce costs, and gain a competitive edge in the pharmaceutical industry. The strong agreement on the readiness to adopt AI technology reflects a growing understanding and appreciation of the potential benefits that these advanced solutions can bring, such as improved demand forecasting, optimized inventory management, and enhanced supply chain visibility. However, the survey results also reveal a smaller proportion of respondents who were neutral (12.20%) or disagreed (9.76% disagreed, 4.88% strongly disagreed) with the assertion, indicating that while the overall sentiment is favourable, there may still be some hesitation or resistance from a minority of stakeholders, potentially due to concerns over implementation challenges, integration issues, or a lack of awareness of the technology's capabilities.

4.4 Reliability

Table 4.8: Reliability Results

Reliability	Cronbach's Alpha
Perceived compatibility	0.9.
Trialability	0.86
Relative Advantage	0.83
Ease of doing business	0.9
Technology export	0.85.
Technology acceptance rate	0.89

The results in Table 4.8 are showing results on reliability. Reliability analysis was conducted using Cronbach's Alpha, a measure of internal consistency that determines if items within a scale assess the same construct. Thus, if Cronbach's alpha falls within the range of $0.8 \leq \alpha < 0.9$, it suggests that the survey instrument demonstrates a high level of internal consistency. Validity refers to the degree to which the research component is meaningful and accurate. The research's validity was ensured by formulating suitable questions for the questionnaire. Table 4.8 is displaying the results of reliability, as measured by the Cronbach alpha coefficient, which fell within the range of 0.8≤ α < 0.9. This range indicates that the survey instrument exhibited a high level of internal consistency. The results demonstrate that all the Cronbach alpha coefficients were satisfactory, suggesting that the scales are appropriate for further analysis. The results suggest that all the Cronbach alpha coefficients are acceptable, suggesting existence of reliability.

4.5 challenges hindering the implementation of AI adoption in the pharmaceutical manufacturing industry in Zimbabwe.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FIN	-0.109899	0.020334	-5.404557	0.0000
CUL	-0.440274	0.205008	-2.147589	0.0388
SEC	-0.218483	0.332079	-0.657923	0.5149
INFR	-0.00326	0.000772	-4.22324	0.0002
REG	-0.02855	0.008606	-3.31703	0.0021

Table 4.8: Challenges to the implementation of AI

Source: Primary data Computations

R^2: 0.920453

ADJ R^2: 0.906817

F Statistic: 67.49900

Prob (F-statistic): 0.000000

The preliminary OLS regression analysis conducted on the challenges hindering the implementation of AI adoption in the pharmaceutical manufacturing industry in Zimbabwe provides valuable insights into the key factors influencing the adoption of AI-powered solutions.

The model's R^2 of 0.920453 indicates that the independent variables (Financial Constraints, Cultural Constraints, Infrastructure Constraints, and Regulations) collectively explain 92.05% of the variation in the dependent variable, AI adoption. The Adjusted R^2 of 0.906817 further suggests that the model has a high goodness of fit, with the independent variables accounting for a substantial proportion of the observed changes in AI adoption. This implies that the selected variables are highly relevant and effective in capturing the drivers and barriers to AI implementation in the Zimbabwean pharmaceutical industry. The F-statistic of 67.49900 and the corresponding Probability (F-statistic) of 0.000000 indicate that the overall regression model is statistically significant at a very high level. This suggests that the independent variables, as a group, have a significant and meaningful impact on the dependent variable, AI adoption, and that the model is a good fit for the data.

4.5.1 Financial Constraints and AI adoption

Financial Constraints had a negative coefficient of -0.109899, a highly significant t-statistic of -5.404557, and a probability value of 0.0000, according to the regression analysis in Table 4.8. This suggests that the deployment of AI technology in Zimbabwe's pharmaceutical manufacturing sector is significantly hampered by cost restrictions.

The negative coefficient suggests that as financial constraints increase, the level of AI adoption decreases proportionally. This finding is consistent with the existing literature on the topic, as evidenced by the corroborating results from the studies conducted by Adekunle et al. (2020) in Nigeria and Smith et al. (2018) in Germany. The high statistical significance of the relationship between financial constraints and AI adoption underscores the critical importance of addressing the financial barriers faced by pharmaceutical manufacturers in Zimbabwe. Factors such as the high costs associated with the acquisition, implementation, and maintenance of AI-powered solutions, as well as the limited access to capital and financial resources, may be hindering the industry's ability to invest in and adopt these transformative technologies.

4.5.2 Cultural Constraints and AI adoption

Cultural barriers significantly impede the adoption of AI-powered solutions, according to the preliminary OLS regression analysis in Table 4.8 on the issues impeding AI adoption in Zimbabwe's pharmaceutical manufacturing sector. The variable's coefficient of -0.440274 shows that adoption of AI declines proportionately with the strength of cultural barriers. The statistical significance of the association between cultural restrictions and AI adoption is indicated at the 5% level by the t-statistic value of -2.147589 and the probability value of 0.0388. These findings support that of a study carried out in Bolivia by Gonzalez et al. (2020), which also indicated that cultural barriers are a major impediment to the industry's adoption of modern technologies like artificial intelligence (AI).

The negative impact of cultural constraints on AI adoption in the Zimbabwean pharmaceutical sector can be attributed to various factors. Resistance to change, a lack of understanding or trust in the technology, and the presence of deeply ingrained beliefs or norms that may be incompatible with the adoption of AI-powered solutions can all contribute to the observed relationship. Additionally, the industry's culture and the mind-set of its key stakeholders, including management, employees, and end-users, can significantly influence the willingness and readiness to embrace AI-driven innovations.

4.5.3 Infrastructure constraints and AI adoption

The findings of the OLS regression on the obstacles to the adoption of AI in Zimbabwe's pharmaceutical manufacturing sector, as shown in Table 4.8, indicate that infrastructure limitations significantly impede the uptake of AI-powered solutions. Infrastructure Constraints has a value of -0.00326, meaning that the degree of AI adoption falls in direct proportion to the number of infrastructure constraints. At the 0.01% level, the association between infrastructure restrictions and AI adoption is statistically significant, according to the t-statistic value of -4.22324 and the probability value of 0.0002. These findings support that of a study carried out in South Africa by Mbeki et al. (2017), which likewise found that a major impediment to the pharmaceutical industry's adoption of AI and other modern technologies is a lack of suitable infrastructure

The negative impact of infrastructure constraints on AI adoption in the Zimbabwean pharmaceutical sector can be attributed to the lack of reliable and high-quality infrastructure required to support the implementation and operation of AI-powered systems. Factors such as limited access to stable electricity, reliable internet connectivity, and secure data storage facilities can all contribute to the observed relationship. Additionally, the lack of specialized technical infrastructure, such as high-performance computing resources and advanced data processing capabilities, can make it challenging for pharmaceutical manufacturers to effectively utilize and integrate AI technologies into their operations.

4.5.4 Regulation and AI adoption

Regulatory restrictions have a major detrimental influence on the adoption of AI-powered solutions, according to the OLS regression analysis in Table 4.8 on the issues impeding the use of AI in Zimbabwe's pharmaceutical manufacturing sector. The variable's coefficient is -0.02855, meaning that adoption of AI declines proportionately as regulatory restrictions gets tighter. The statistical significance of the relationship between regulatory limitations and AI adoption is indicated at the 1% level by the t-statistic value of -3.31703 and the probability value of 0.0021. This finding supports the findings of a research carried out in China by Li et al. (2020), which also pointed to regulatory hurdles as a major obstacle preventing the pharmaceutical business from adopting cutting-edge

The negative impact of regulatory constraints on AI adoption in the Zimbabwean pharmaceutical sector can be attributed to the complex and often restrictive regulatory environment in which the industry operates. Factors such as outdated or unclear regulations, lengthy approval processes, and a lack of regulatory guidance on the use of AI-powered solutions can all contribute to the observed relationship. Additionally, the pharmaceutical industry is subject to stringent regulations and compliance requirements, which may create a risk-averse culture and make pharmaceutical manufacturers hesitant to invest in and implement AI technologies that may not yet be fully integrated into the existing regulatory framework.

4.6 Chapter Summary

This chapter examined the key factors influencing the adoption and implementation of artificial intelligence (AI) technologies within the pharmaceutical manufacturing industry in Zimbabwe. The regression analysis reveals that regulatory constraints and infrastructure limitations have a significant negative impact on AI adoption, corroborating findings from previous studies in similar contexts. These insights provide valuable guidance for policymakers and industry stakeholders in Zimbabwe, highlighting the need to address regulatory and infrastructure-related challenges to foster the widespread adoption of AI-powered solutions and enhance the competitiveness and efficiency of the pharmaceutical manufacturing sector. The next chapter will present the study summary, conclusions, recommendations and suggestions for future study.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

Building on the findings and analyses presented in the previous chapter, this final chapter of the study provides a summary of the key research outcomes, draws overarching conclusions, and outlines the policy implications and recommendations for the pharmaceutical manufacturing industry in Zimbabwe. The chapter will synthesize the findings, distil the core conclusions, and delineate the practical implications for policymakers, industry stakeholders, and pharmaceutical manufacturers. Finally, the introduction outlines the chapter's structure, which includes sections devoted to the study summary, concluding remarks, policy implications and recommendations, and suggestions for future research directions, all of which are aimed at guiding the industry's efforts to enhance the adoption and integration of AI-powered solutions and unlock the transformative potential of this emerging technology within the Zimbabwean pharmaceutical manufacturing landscape.

5.2 Study Summary

This research study's main goal was to investigate the difficulties in implementing artificial intelligence (AI) in Zimbabwe's pharmaceutical manufacturing sector. The researchers used a mixed-methods research design, including quantitative and qualitative data gathering and analysis methodologies, to accomplish this goal. The study's secondary goals were to: (i) determine the degree of AI adoption in Zimbabwe's pharmaceutical manufacturing sector, taking into account variables like trialability, relative advantage, ease of doing business, technology acceptance rate, and perceived compatibility; and (ii) investigate the obstacles to AI adoption in the sector.

The study's quantitative component utilized an OLS regression model to investigate the relationships between AI adoption and various factors. The preliminary results revealed a strong and statistically significant relationship, with an R-squared value of 0.920453 and an adjusted R-squared of 0.906817. This suggests that the independent variables (Financial Constraints, Cultural Constraints, Infrastructure Constraints, and Regulations) collectively explain a substantial proportion of the variation in AI adoption within the Zimbabwean pharmaceutical manufacturing industry.

The reliability analysis conducted using Cronbach's Alpha demonstrated a high level of internal consistency, with the alpha coefficients falling within the range of $0.8 \leq \alpha < 0.9$. This indicates that the survey instrument used in the study exhibited a high level of reliability. Additionally, the validity of the research was ensured through the formulation of appropriate questions for the questionnaire.

Further analysis delved into the specific challenges hindering the implementation of AI adoption. The regression results showed that financial constraints, cultural constraints, infrastructure limitations, and regulatory challenges have a significant negative impact on the industry's ability to integrate AI technologies. The high F-statistic of 67.49900 and the corresponding Probability (F-statistic) of 0.000000 suggest that the overall regression model is statistically significant at a very high level, indicating that the independent variables, as a group, have a significant and meaningful impact on AI adoption in the Zimbabwean pharmaceutical industry.

5.3 Conclusion

The findings of this study on the adoption of artificial intelligence (AI) in the pharmaceutical manufacturing industry in Zimbabwe provide a clear and well-substantiated understanding of the key challenges and barriers hindering the successful integration of these transformative technologies. The research demonstrates that financial constraints, cultural barriers, infrastructure limitations, and regulatory hurdles collectively exert a significant and negative impact on the industry's ability to embrace AI-powered solutions. The high explanatory power of the regression model, coupled with the robust reliability and validity of the survey instrument, lend credence to the study's conclusions. These insights underscore the critical need for targeted interventions, policy reforms, and strategic investments to address the identified impediments and catalyse the widespread adoption of AI in the Zimbabwean pharmaceutical manufacturing sector. By tackling these multifaceted challenges, the industry can unlock the transformative potential of AI, enhance its global competitiveness, and deliver innovative, high-quality products to the benefit of healthcare systems and patients nationwide.

5.4 Policy Implications and Recommendations

Based on the findings of the study examining the challenges in the adoption of AI in the pharmaceutical manufacturing industry in Zimbabwe, the following policy recommendations are proposed:

1. Establish a Pharmaceutical Innovation Fund: The government should create a dedicated Pharmaceutical Innovation Fund to provide financial incentives, grants, and low-interest loans to pharmaceutical manufacturers for the acquisition, integration, and implementation of AI-powered technologies. This targeted funding mechanism will help address the significant financial constraints identified as a key barrier to AI adoption.

2. Develop AI-Focused Skill-Building Programs: In partnership with academic institutions and industry associations, the government should invest in comprehensive skill-building programs to enhance the digital and technological capabilities of the pharmaceutical workforce. This will involve training programs, industry-academia collaborations, and talent development initiatives to address the cultural constraints and build a strong talent pool capable of driving AI adoption.

3. Upgrade Industrial Infrastructure: The government should prioritize the modernization and upgrading of industrial infrastructure, including reliable power supply, high-speed internet connectivity, and specialized manufacturing facilities. This will help overcome the infrastructure constraints that currently impede the implementation of AI technologies in the pharmaceutical industry.

4. Streamline Regulatory Frameworks: Policymakers should undertake a comprehensive review of the existing regulatory environment and implement reforms to streamline the approval processes, reduce administrative complexities, and align the regulatory landscape with the evolving technological landscape. This will help mitigate the regulatory constraints and create an enabling environment for AI adoption.

5. Establish an AI Advisory Council: The government should constitute an AI Advisory Council comprising industry experts, academic researchers, and regulatory authorities to provide guidance, facilitate knowledge-sharing, and develop a comprehensive roadmap for the

systematic integration of AI in the pharmaceutical manufacturing sector. This collaborative approach will help address the multifaceted challenges and drive sustainable AI adoption.

The successful implementations of the proposed policy recommendations, the Zimbabwean government can create a conducive ecosystem that empowers pharmaceutical manufacturers to overcome the identified barriers and harness the transformative potential of artificial intelligence. This holistic approach will contribute to the industry's global competitiveness, enhance product quality and patient outcomes, and position Zimbabwe as a leader in the adoption of advanced technologies in the pharmaceutical sector.

5.5 Suggestions for Future Studies

Building upon the findings of the study on the challenges in the adoption of AI in the pharmaceutical manufacturing industry in Zimbabwe, several avenues for future research are recommended. A longitudinal analysis tracking the progression of AI adoption over an extended period would provide valuable insights into the dynamic nature of the challenges and the industry's response to policy interventions. Expanding the scope to include a comparative analysis with other developing economies or regional counterparts would offer a broader perspective on the common impediments, best practices, and emerging trends. Complementing the quantitative findings, future research could delve deeper into the qualitative aspects through in-depth interviews, focus group discussions, and case studies to provide a richer understanding of the nuanced, context-specific factors influencing the industry's decision-making. Additionally, extending the research to encompass other key sectors, such as healthcare or medical devices, would generate a more comprehensive understanding of the cross-sectoral challenges and opportunities in AI adoption, enabling policymakers to develop holistic strategies for the broader life sciences ecosystem. By pursuing these future research directions, scholars and industry researchers can build upon the solid foundation established by this study, informing strategic decisions and unlocking the transformative potential of AI technologies in Zimbabwe and beyond.

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APPENDICES

Research Questionnaire

Greetings! Thank you for agreeing to complete this questionnaire. We are interested in measuring the adoption of AI and the challenges that affects AI adoption of your organization.

My name is **Chakonza Takudzwa** currently doing my Master's degree at **Bindura University of Science Education** in Bindura, Zimbabwe. I am conducting research on 'Challenges in the adoption of Artificial intelligence in the pharmaceutical manufacturing industry in Zimbabwe.'.

All information you provide on this survey will be kept private and will not in any way be linked to you. The personal information you provide will be used and disclosed only for the purpose of this survey. The protection of your personal information is very important to us in order to gain your trust and participation. Your participation is greatly appreciated and will help us improve on future research. This questionnaire consists of 3 sections, which will take approximately 5-8 minutes of your precious time to complete.

For further information, please do not hesitate to contact me on:

takudzwachakonza5@gmail.com

+263782 836 039

Section A

General Information

Please tick your responses

Nature of pharmaceutical manufacturing company

- ☐ Research and Development Company.
- ☐ Contract manufacturing organization.
- ☐ Generic manufacturing company
- ☐ Specialty pharmaceutical company
- ☐ Others

Number of years in business

- ☐ Less than 2 year
- ☐ 2-4 years
- ☐ 4-6 years
- ☐ 6-8 years
- ☐ 8 and above

Organization size

- ☐ Less than 50 employees
- ☐ 50-100 employees
- ☐ 100-150 employees
- ☐ More than 150 employees

Section B

Please tick your responses

Use the following five-point Likert scale as adopted with the responses strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5).

Perceived Compatibility

	1	2	3	4	5
AI technologies are compatible with the current industrial systems					
AI technologies are compatible with the supply chain styles and strategies					
AI technology is not consistent with the current supply chain platforms.					

Trialiability

	1	2	3	4	5
AI technology provides chances for future usages					
AI technology helps in assessing future supply chain tasks					
AI is innovative because it provides chances to have rich content in supply chain content in supply chain settings.					

Relative advantage

	1	2	3	4	5
AI technology provides more supply chain features than old ones					
AI technology helps me to save time and effort, as compared with old systems					
AI technology is not consistent with the current supply chain platforms.					

Ease of Doing Business

	1	2	3	4	5
AI technology is preferred by supply chain managers and staff					
AI technology is known by many adopters in our organisation.					
AI technology is widely accepted at the institutional level					

Technology Export

	1	2	3	4	5
AI technology innovation features are highly demanded at the institutional level					
IA technology satisfies the organisation needs; it was invented by other countries.					
IA technology does not satisfy the supply chain staff needs.					

Technology acceptance rate

	1	2	3	4	5
Institutions are willing to upgrade their supply chain platforms and ready to include AI as part of it.					
Institutions are ready to adopt AI technology for supply chain purposes					

Section C

Challenges Hindering AI adoption

Please tick your responses

Use the following five-point Likert scale as adopted with the responses strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5).

Culture

	1	2	3	4	5
I feel connected to the work I do					
I feel the organization prioritizes diversity, equity, and inclusion					
I know where and how to report concerns about harassment and discrimination					
I feel a sense of belonging at work					
I feel recognized and appreciated for my contributions to the organisation					
I feel leaders and managers are transparent					

Security

	1	2	3	4	5
We use encryption technologies to protect sensitive data					
Our IT team carry out regular vulnerability tests on our systems.					
We have AI systems to protect us from cyber threats and intellectual property theft					
We have a recovery arrangements in place in the event of an IT infrastructure incident					

AI knowledge and Financial

	1	2	3	4	5
AI can be biased in decision-making					
AI will replace human jobs in the future					

I trust AI systems with our personal data					
AI can improve our daily life					
We afford top AI systems					

‘

AI Infrastructure

	1	2	3	4	5
We have enough AI infrastructure					
Our data infrastructure is powerful and fast					
We have access to reliable internet connectivity					
We can afford powerful AI infrastructure					
We have AI expertise, experience, and talent					

AI Regulations

	1	2	3	4	5
Our AI processes comply with data protection laws					
AI should be regulated by governments					
There are stringent AI regulatory requirements					
There are enough enforcement mechanisms to supervise AI users					
I am worried about privacy regulations and ethical considerations of AI					

============================ *The end* ================================

Thank you for participating in this study!!!!!!!!!!!!!!!!

CONSENT FORM

Tittle of study: Challenges in the adoption of Artificial intelligence in the pharmaceutical manufacturing industry in Zimbabwe

Investigator: Chakonza Takudzwa

Introduction

You are being asked to participate in a research study to determine challenges in the adoption of Artificial intelligence in the pharmaceutical manufacturing industry in Zimbabwe.

You were selected as a possible participant because you have the information needed by the principal investigator.

We ask that you read this form and ask any questions that you may have before agreeing to be in the study.

Purpose of study

The aim of this study is to examine the challenges in the adoption of AI in the pharmaceutical manufacturing industry in Zimbabwe.

This research may be published in peer-review journals and books, and be presented in workshops, seminars or conferences.

Description of the Study Procedures

If you agree to be in this study, you will be asked to answer truthfully three sections the questionnaire containing questions that are related to the challenges of the adoption of AI.

Risks/Discomforts of Being in this Study

There are no expected risks.

Benefits of being in the study

Participation is voluntary, with no incentives given for completing the survey.

Confidentiality

Information obtained from this study will be kept strictly confidential. We will not include any information in any report that will make it possible to identify you.

Payments

There will not be any payment received or charged for participating in this study

Right to refuse or withdraw

Participating in this study is entirely optional. You may refuse to participate in this study at any time and this will not affect your relationship with the investigators of this study.

Right to Ask Questions and Report Concerns

You have the right to ask questions concerning this research and to have those questions answered by the investigator at any point and further questions, contact Chakonza Takudzwa at takudzwachakonza5@gmail.com or +26378 283 6039/+26371 523 0872

Consent

- Your signature below indicates that you have decided to volunteer as a participant in this study, and that you have read and understood the information provided above

Subject's Signature: ______________________ Date: ______________