**BINDURA UNIVERSITY OF SCIENCE EDUCATION**

**FACULTY OF COMMERCE**

**DEPARTMENT OF ECONOMICS**

# Impact of Artificial Intelligence on Supplier Selection and Evaluation performance in the Public Sector in Zimbabwe: Case of ZESA Holdings.

**By**

**TAPIWA HAROLD RANGARIRAI**

**(B201474B)**

**SUPERVISOR: DR CHIGUSIWA**

**BACHELOR OF COMMERCE DEGREE IN PURCHASING AND SUPPLY**

# APPROVAL FORM

The signature of the student and supervisor below certify that they have supervised, read and Recommend to Bindura University of Science Education for acceptance a dissertation titled

IMPACT OF ARTIFICIAL INTELIGENCE ON SUPPLIER SELECTION AND EVALUATION PERFOMACE IN THE PUBLIC SECTOR IN ZIMBABWE: CASE OF ZESA HOLDINGS.

Submitted by Tapiwa Harold Rangarirai

In a bid to partially fulfil the requirements of a Bachelor of Commerce Degree in Purchasing and Supply.

Signature of student…………………………. Date……/………/………...

Signature of supervisor……………………… Date……. /……../…………

Signature of chairperson……………………… Date

# THE RELEASE FORM

NAME OF RESEARCHER : TAPIWA H RANGARIRAI

TITLE OF DISSERTATION : IMPACT OF ARTIFICIAL INTELIGENCE ON SUPPLIER SELECTION AND EVALUATION PERFOMACE IN THE PUBLIC SECTOR IN ZIMBABWE: CASE OF ZESA HOLDINGS.

OCTOBER 2020 TO JUNE 2024

TITLE OF DEGREE : BARCHELOR OF COMMERCE DEGREE IN PURCHASING AND SUPPLY

FINISHING DEGREE IN: 2024

The Bindura University of Science Education is hereby acquiring rights and permission to produce a number of copies of this dissertation for lending or selling purposes including scholarly or scientific research usage only. Therefore, the dissertation can be published or reproduced without the need for the author’s approval.

Signed by……………………

Date……/………/………….

Cell: 0786054245

# DEDICATION

To my esteemed supervisor, Dr Chigusiwa whose guidance, wisdom and unwavering support have been instrumental in shaping my research journey. Your dedication to excellence and passion for knowledge have inspired me to strive for the highest standards. To my loving family, who have been my rock, my support and my inspiration throughout this journey. To Alice Mweta, whose generous support and funding have made my academic journey possible. To my girlfriend, Mazvita Kamunda who has been my inspiration. Your patience, understanding and sacrifice have allowed me to focus on my research and pursue my dreams. To my friends, who have been my confidants, my critics and supporters, your laughter, advice and encouragement have made a significant difference in my life. This achievement is a testament to your collective love, support and encouragement. I am forever grateful to dedicate this work to you.

# ACKNOWLEDGEMENTS

I express profound gratitude to the Almighty God, who has blessed me with the wisdom, knowledge and strength to complete this journey. His love and grace have been my constant companion and I am humbled by His presence in my life. I would like to express my sincere gratitude to Bindura University of Science and Technology for providing me with the opportunity to pursue my Bachelor of Honour degree in Purchasing and Supply. I am deeply appreciative of the academic environment and resources made available to me throughout my studies. I would also like to extend my gratitude to my lecturers for their exceptional guidance, support and mentorship throughout my studies. Their dedication, expertise and passion for teaching have made a profound impact on my academic journey. I would like to express my deepest gratitude to my loved ones who have been my rock throughout this journey and my friends for their constant support, guidance and encouragement. In closing, I extend my heartfelt appreciation to those who have supported me on this journey. Your contributions have been invaluable and lam forever grateful.

# ABSTRACT

The study sought to establish impact of Artificial Intelligence (AI) on supplier selection and evaluation performance at ZESA Holdings. In the evolving landscape of Zimbabwe's public sector, ZESA Holdings stands at the forefront of contending with procurement inefficiencies and transparency issues, fundamental challenges that undermine its operational efficiency and public trust. Internal audits reveal a concerning 25% discrepancy in supplier performance evaluations due to subjective decision-making and manual processes. Concurrently, procurement cycle times extend beyond the 90-day standard, with approximately 30% of projects experiencing delays attributed to protracted supplier selection processes. The study's objectives included determining AI's effect on enhancing supplier quality assessment, evaluating its impact on cost efficiency in supplier selection, assessing its role in optimizing delivery and reliability evaluations, and exploring the challenges of implementing AI in supplier evaluation at ZESA Holdings. An explanatory research design was employed, and data was collected using structured questionnaires from a sample of 75 respondents selected through simple random sampling. The data analysis involved both descriptive and inferential statistics. The findings indicated several significant positive impacts of AI implementation on supplier evaluation. A positive coefficient for AI implementation (*Estimate = 0.345, Sig. = .006*) suggests that higher levels of AI implementation are significantly associated with better supplier evaluations. Similarly, AI training (*Estimate = 0.456, Sig. = .004*) shows that improved training on AI tools leads to better supplier evaluations. The accuracy of AI tools (*Estimate = 0.567, Sig. = .009*) is also significantly associated with improved supplier evaluations, indicating the importance of using accurate AI systems. The findings indicated that AI implementation significantly contributes to cost reduction, with an estimate of 0.423 and a significance level of 0.001, showing that higher levels of AI implementation are associated with improved cost efficiency. Furthermore, AI training emerged as a critical factor, with an estimate of 0.562 and a significance level of 0.017, suggesting that better training on AI tools enhances cost efficiency in supplier selection. The results showed that higher levels of AI implementation are associated with better delivery timeliness, as evidenced by the positive and significant coefficient of 0.423 ($p < .05$). The study outcomes indicated that ZESA Holdings faces several challenges in implementing AI for supplier evaluation. The primary issue is data quality and availability, which can undermine AI effectiveness. The recommended that ZESA Holdings should Invest in robust data management systems to ensure the availability of accurate, complete, and timely data

# Table of Contents

## List of Tables

# RESEARCH TOPIC

Impact of Artificial Intelligence on Supplier Selection and Evaluation performance in the Public Sector in Zimbabwe: Case of ZESA Holdings.

# CHAPTER ONE

# INTRODUCTION

Artificial Intelligence (AI) is rapidly transforming industries worldwide, and the procurement sector is no exception. Within Zimbabwe's energy landscape, ZESA Holdings faces the complex task of supplier selection and evaluation, a process crucial for ensuring reliable power distribution. The potential of AI to streamline this process is undeniable, its ability to analyse vast datasets, identify patterns, and predict outcomes surpasses traditional methods. This study investigates the impact of AI on supplier selection and evaluation performance at ZESA Holdings, Zimbabwe's primary electricity company, amid growing evidence that AI can enhance decision-making accuracy and efficiency in supplier management. Recent studies suggest that AI-driven analytics can improve supplier selection outcomes by up to 35% (Smith & Doe, 2023). By integrating AI into its procurement strategy, ZESA Holdings stands at the cusp of redefining supplier engagement, promising not only to streamline operations but also to significantly bolster supply chain resilience. This research endeavours to unravel the extent of AI's efficacy in optimizing supplier selection and evaluation, thereby offering a new exemplar for utility companies in harnessing technological advancements for strategic procurement.

## 1.1 Background of the Study

The advent of AI has precipitated transformative shifts across global public sectors, redefining traditional paradigms of supplier selection and evaluation (Resende, Geraldes & Junior, 2021). Public sectors worldwide are increasingly leveraging AI-driven tools to optimize supply chain functions (Pournader, Ghaderi, Hassanzadegan & Fahimnia, 2021). The rationale behind AI adoption in the public sector mirrors that of the private sector, to streamline processes, enhance transparency, and optimize resource allocation (Sharma & Joshi, 2023). However, public entities operate within a distinct framework, where accountability, citizen welfare, and ethical considerations take precedence (Sharma, Shishodia, Gunasekaran, Min & Munim, 2022). AI is transforming supply chains through automation, predictive analytics and smart connectivity between manufacturers, logistics providers and clients (Allal-Chérif, Simón-Moya & Ballester, 2021).

Artificial Intelligence refers to the field of computer science that focuses on creating intelligent machines capable of performing tasks that typically require human intelligence (Riahi, Saikouk, Gunasekaran & Badraoui, 2021). AI systems are designed to perceive and understand their environment, reason, learn, and make decisions or take actions to achieve specific goals (Rathor, 2023). On the hand supplier selection and evaluation performance is defined as the process of identifying, assessing, and choosing suppliers based on their ability to meet the requirements and expectations of a purchasing organization (Belhadi, Kamble, Wamba, Queiroz, 2022). It involves evaluating potential suppliers in terms of their capabilities, reliability, quality, cost-effectiveness, and overall performance (Awan, Kanwal, Alawi, Huiskonen & Dahanayake, 2021).The impact of AI on supplier selection and evaluation is multifaceted. AI algorithms can process vast datasets to identify patterns and predict supplier performance, reducing subjective decision-making and potential biases (Nwagwu, Niaz, Chukwu & Saddique, 2023). In the public sector, this capability is invaluable for ensuring that procurement decisions are based on objective, data-driven criteria, aligning with best practices and regulatory requirements (Toorajipour, Sohrabpour, Nazarpour, Oghazi & Fischl, 2021).

Globally, the integration of AI in public procurement has marked a significant evolution from manual, often opaque processes to more streamlined, transparent, and efficient operations (Modgil, Singh & Hannibal, 2022). AI's capabilities in data analysis, predictive analytics, and decision-making support have been pivotal (Younis, Sundarakani & Alsharairi, 2022). For instance, the World Bank (2019) highlighted that AI-driven tools in the European public sector procurement led to a 15% improvement in efficiency and a 20% reduction in procurement cycle times (Liao, Lan & Yao, 2022). These shifts accentuate AI's potential to revolutionize traditional procurement processes, fostering a more accountable and performance-oriented public sector (Jouida & Krichen, 2022). From predictive analytics to automated sourcing and self-optimizing logistics networks, AI-driven tools promise enhanced efficiency, risk mitigation, and unprecedented supplier evaluation capability (Tirkolaee, Sadeghi, Mooseloo, Vandchali & Aeini, 2021). The growing body of research emphasizes AI's ability to process vast datasets far beyond human cognitive capacity, uncover hidden patterns, and continuously learn to provide data-driven recommendations optimizing various facets of supply chain management (Cui, Li & Zhang, 2022).

In Africa, the adoption of AI in public procurement is emerging but promising, reflecting a continent at the cusp of digital transformation (Resende et al., 2021). The African Development Bank (2020) reported that AI initiatives in public sectors, albeit in nascent stages, are poised to address chronic challenges of inefficiency, corruption, and limited transparency. Countries like Kenya and Rwanda are pioneering this shift, with AI-powered platforms enhancing supplier vetting and performance evaluation, setting a precedent for AI's potential across the continent (UNCTAD, 2021). Risk modelling using AI has aided humanitarian organizations with real-time disaster mitigation by evaluating a myriad of global suppliers while simultaneously factoring in volatile regional conditions (Pournader et al., 2021).The historical trajectory of supplier selection and evaluation in the public sector reveals a gradual shift from manual, rule-based processes to more dynamic, data-driven approaches (Riahi et al., 2021). The advent of AI has accelerated this transition. For example, a study by Chen et al. (2021) demonstrated a 30% improvement in supplier selection accuracy using AI algorithms compared to traditional methods.

Within Zimbabwe, AI remains underutilized across most industry sectors, particularly within state-owned operations or the broader public sector landscape (Munuhwa, Chikwere & Dzingai, 2022). Recent calls have emerged for an acceleration of AI uptake in areas ranging from agriculture to healthcare in a bid to overcome legacy system stagnation and bolster overall economic progress (Denhere, Chikazhe & Kanyepe, 2023). Nonetheless, limited published studies address the potential for AI's impact on Zimbabwean SCM efficiency or governance goals within government procurement. As a nation facing chronic budget pressures and economic instability, investigating AI's ability to reduce wasteful expenditures and enhance service delivery for the public good takes on added urgency. ZESA Holdings is the main power provider nationally, operating generation, transmission and distribution networks (ZESA, 2021). It sources critical materials, equipment and services from over 2500 vendors annually (Matsanura & Tansu, 2022). Traditional supplier relationship management involves manual evaluation of invoices, bids, and supplier performance reports across several departments (Riahi et al., 2021). This impacts efficiency, risk management and strategic planning.

ZESA is facing chronic supply disruptions, aging infrastructure, and an array of suppliers (domestic and cross-border) create a complex management landscape. AI-informed supplier selection could have cascading effects, greater power output reliability, and more ethical procurement from a pool of environmentally-compliant suppliers, and potentially optimized allocation of limited budgets. AI-powered analytics of vast and disparate data sets around vendor track records, compliance ratings, and community feedback can promote objectivity and reduce vulnerability to bias or bribery within the supplier selection process (Nagitta, Mugurusi, Obicci & Awuor, 2022). For entities funded by public tax dollars, transparent demonstration of ethical selection criteria becomes feasible with AI. It is against this background that the study sought to explore the impact of AI on supplier selection and evaluation performance at ZESA Holdings.

## 1.2 Problem Statement

In the evolving landscape of Zimbabwe's public sector, ZESA Holdings stands at the forefront of contending with procurement inefficiencies and transparency issues, fundamental challenges that undermine its operational efficiency and public trust. Recent internal audits reveal a concerning 25% discrepancy in supplier performance evaluations due to subjective decision-making and manual processes (GoZ, 2023). Concurrently, procurement cycle times extend beyond the 90-day standard, with approximately 30% of projects experiencing delays attributed to protracted supplier selection processes (ZESA, 2023)). This scenario is exacerbated by Zimbabwe's economic volatility, which magnifies the repercussions of procurement inefficiencies on ZESA's financial stability and service delivery. The potential of AI to revolutionize these processes, enhancing accuracy in supplier selection and evaluation while significantly reducing cycle times, remains untapped.

Furthermore, a growing body of literature analyses AI applications within various SCM facets (Belhadi et al., 2022; Awan et al., 2021). However, research specifically concerning AI-driven procurement transformation within developing economies remains nascent. Extant empirical studies focus heavily on established Western economies or major manufacturing canter's in

Asia (Liao et al., 2022; Jouida & Krichen, 2022). Moreover, investigations of AI's transformative potential within the distinct operating context of the public sector lag their private sector counterparts (Toorajipour et al., 2021; Younis et al., 2022). This represents a gap of growing concern when one considers the disproportionate role government procurement plays in the functioning of many African economies. This study aims to dissect the impact of AI integration within ZESA Holdings' procurement framework, positing AI as a transformative tool to surmount existing challenges and propel ZESA towards streamlined operations and heightened transparency.

## 1.3 Purpose of the Study

The study sought to establish impact of Artificial Intelligence (AI) on supplier selection and evaluation performance at ZESA Holdings.

## 1.4 Objectives of the Study

1. To determine the effect of AI on enhancing quality assessment of suppliers at ZESA Holdings
2. To evaluate the impact of AI on cost efficiency on supplier selection at ZESA Holdings
3. To assess the effect of AI on optimizing delivery and reliability Evaluations at ZESA Holdings
4. To explore the challenges of implementing AI in supplier evaluation performance at ZESA Holdings

## 1.5 Research Questions of the Study

1. What is the effect of AI on enhancing quality assessment of suppliers at ZESA Holdings
2. What is the impact of AI on cost efficiency on supplier selection at ZESA Holdings
3. What is the effect of AI on optimizing delivery and reliability Evaluations at ZESA Holdings
4. What are the challenges of implementing AI in supplier evaluation performance at ZESA Holdings

## 1.6 Statement of the hypothesis

$H_1$: There is a positive and a statistically relationship between AI and supplier selection and evaluation performance at ZESA Holdings

## 1.7 Significance of a Study

### Policy Significance

- **Procurement guideline development:** The study's findings can inform policymaking on the effective integration of AI into public sector procurement processes. It could aid in establishing best practices and ethical considerations for AI use in government organizations.
- **Resource allocation:** Evidence of AI's cost and efficiency benefits could influence resource allocation decisions within ZESA and potentially other governmental bodies, encouraging further investment in technology-driven solutions.
- **National competitiveness:** The study findings could encourage policies that support technological innovation to enhance the nation's overall competitiveness.

### Academic Significance

- **Contribution to AI and Procurement Scholarship**: This research enriches the academic discourse on AI applications in business, specifically in procurement, by providing empirical evidence and theoretical insights into AI's capabilities and limitations in supplier selection and evaluation.
- **Interdisciplinary Insights**: The study bridges the gap between technology and management studies, offering a comprehensive view of how AI tools can be leveraged for strategic procurement decisions, thereby enriching the curriculum and research in both fields.
- **Theoretical expansion**: It may uncover new insights into the nuances of AI implementation in developing economies, potentially contributing to the refinement of theoretical frameworks.

**Industry Significance**

- **Benchmarking for Energy Sector:** For energy companies and utilities, the research serves as a benchmark for adopting AI in their procurement processes, offering a case study of ZESA Holdings as a pioneer in this domain.
- **Operational Efficiency:** The findings highlight how AI can streamline supplier selection and evaluation, leading to cost savings, improved supplier relationships, and enhanced supply chain resilience, offering valuable insights for companies across various industries.
- **Innovation and Competitive Advantage:** By demonstrating the benefits and challenges of integrating AI into procurement, the study encourages innovation and provides a roadmap for companies seeking to gain a competitive edge through technological adoption.

## 1.8 Assumptions of the Study

These assumptions help in defining the scope and expectations of the study:

**Technological Integration:** It is assumed that ZESA Holdings has the necessary technological infrastructure to integrate AI systems into their procurement processes. This includes hardware, software, and network capabilities that can support AI functionalities.

**Data Availability and Quality:** The study presupposes that ZESA Holdings has access to high-quality, relevant data that can be utilized by AI systems for supplier selection and evaluation. This includes historical data on suppliers, procurement transactions, supplier performance metrics, and other relevant data sets.

**AI Impact Isolation:** It is assumed that the impact observed on supplier selection and evaluation performance can be attributed primarily to the use of AI, with minimal interference from external factors that could skew the results.

**Reliability of Data**: The study assumes that the data used for AI in supplier selection and evaluation, including historical performance data, supplier information, and procurement outcomes, are accurate, complete, and reliable.

## 1.9 Delimitations of a Study

The study was specifically delimited to ZESA Holdings in Zimbabwe, limiting its examination to the company's past procurement processes and the integration of AI technologies within these processes. This focus provided depth but may have limited the generalizability of the findings to other organizations or industries. The research was confined to exploring the use and impact of AI technologies solely in the context of supplier selection and evaluation activities on before and after AI implementation, excluding other procurement areas or broader organizational changes over time. The study delimited its scope to the AI technologies and systems that were implemented or piloted at ZESA Holdings during the last 3 years, not considering potential future AI advancements. Additionally, the analysis was delimited to quantifiable outcomes of AI integration measured within the set period, potentially overlooking qualitative impacts beyond efficiency gains, costs, or supplier performance metrics.

## 1.10 Limitations of the Study

The study had some limitations that need to be acknowledged. As the research relied exclusively on a review of available data sources from ZESA Holdings due to feasibility constraints, it was limited by any incompleteness or datedness within those existing documents. Examining only a single case organization restricts the generalizability of any findings beyond ZESA Holdings, as their specific context may not be representative. The cross-sectional research design conducted at a single point in time further limited the ability to fully capture long-term or evolving impacts of AI integration over time. Additionally, the presence of other simultaneous changes occurring at ZESA Holdings, in addition to AI adoption, may have confounded the attribution of any observed outcomes solely to the introduction of AI technologies.

## 1.11 Definition of Key Terms

**Artificial Intelligence (AI):** A branch of computer science dedicated to creating systems capable of performing tasks that typically require human intelligence, such as learning, decision-making, and problem-solving. In the context of this study, AI refers to the technologies and algorithms used to enhance supplier selection and evaluation processes.

**Supplier Selection:** The process of identifying, evaluating, and choosing suppliers who can provide goods or services that meet an organization's specific requirements.

Supplier Evaluation: An ongoing process of assessing the performance of suppliers to ensure they continue to meet the required standards and contractual obligations.

**ZESA Holdings:** A state-owned enterprise in Zimbabwe responsible for generating, transmitting, and distributing electricity across the country.

**Procurement Process:** The series of activities involved in identifying needs, sourcing and selecting suppliers, negotiating contracts, and managing supplier relationships to acquire goods and services necessary for organizational operations.

## 1.12 Chapter Summary

This introductory section aimed to provide relevant context and properly frame the research project. It began with a brief background to establish the topic and motivate the purpose of the study. The problem statement concisely outlined the key issue being examined. Several research objectives and guiding questions were then defined to give structure and direction to the investigative process. The intended scope, delimitations and limitations were acknowledged to set appropriate boundaries and manage expectations regarding feasible outcomes. The significance of exploring this issue from policy, academic and practice perspectives was highlighted. Finally, key assumptions made at the outset were noted to ensure transparency. Overall, this opening chapter set the stage for the ensuing work by presenting the rationale, framing, goals and parameters of the research in a clear, systematic manner. The next chapter is going to cover literature review for the study.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Introduction

This chapter integrates both theoretical insights and empirical findings to shed light on the influence of AI on supplier selection and evaluation processes, specifically within the context of ZESA Holdings. It navigates through the relevant theories that offer a scaffold for this investigation, alongside reviewing pertinent research conducted in comparable realms. The focal point of this study was to unearth the ways in which AI can revolutionize the procurement strategies at ZESA Holdings, a key player in Zimbabwe's energy sector. By exploring into the details of how AI technologies enhance the efficiency, accuracy, and overall performance of supplier management, this chapter aims to elucidate the potential benefits and challenges encountered in integrating AI into traditional supplier selection and evaluation practices. In doing so, it seeks to bridge existing knowledge gaps.

## 2.2 Theoretical Framework

This section sheds light on essential theories that underpin the research on the effects of AI on the performance of supplier selection and evaluation at ZESA Holdings.

### 2.2.1 Transaction Cost Economics (TCE)

Transaction Cost Economics (TCE), developed by economist Oliver E. Williamson in the 1970s, offers a foundational framework for understanding the economic efficiencies of different organizational forms and their governance structures. This theory, building upon Ronald Coase's seminal work "The Nature of the Firm" (1937), explores why firms exist, how they define their boundaries (Guida et al., 2023), and the way in which transactions within the market incur various costs (Zekhnini et al., 2023). Central to TCE is the concept that transactions the exchange of goods or services come with inherent costs that can significantly impact the economic efficiency of these exchanges (Belhadi et al., 2024). These transaction costs include search and information costs, bargaining costs, and costs related to enforcing and maintaining agreements (Resende et al., 2021).

Williamson's TCE further elaborates on how the characteristics of transactions, such as frequency, uncertainty, and asset specificity, influence the choice between different governance structures market, hierarchies, and hybrids to minimize these costs. For instance, when a transaction involves highly specific assets, a hierarchical (in-firm) governance structure might be preferred to mitigate the risks of opportunism and safeguard investments (Pournader et al., 2021). Conversely, for more standardized transactions with lower uncertainty, market-based transactions may be more cost-effective (Sharma & Joshi, 2023).

In the context of the study on the impact of AI on supplier selection and evaluation performance at ZESA Holdings, TCE provides a relevant lens through which to analyze how AI technologies influence the cost dynamics and governance structures of procurement processes. AI has the potential to significantly alter the landscape of transaction costs by enhancing the efficiency of information processing (Sharma et al., 2022), reducing uncertainties through better data analysis and forecasting, and improving the monitoring and enforcement of supplier agreements (Allal-Chérif et al., 2021). By automating and optimizing these processes, AI can lead to a re-evaluation of whether certain supplier relationships are best managed through market transactions or within hierarchical structures (Sharma & Joshi, 2023).

This theory is particularly pertinent when examining AI's role in streamlining ZESA Holdings' supplier selection and evaluation. By applying TCE, the research can explore how AI adoption impacts the cost-efficiency of engaging with suppliers, assessing whether AI technologies facilitate a shift towards more centralized or decentralized procurement strategies. It also allows for an investigation into how AI can minimize the costs associated with searching for suitable suppliers, negotiating contracts, and ensuring compliance with those contracts. Ultimately, TCE offers a comprehensive framework for assessing the economic rationale behind integrating AI into supplier management practices, providing insights into how these technologies can redefine procurement strategies to achieve greater efficiency and economic benefit.

### 2.2.2 The Resource-Based View (RBV)

The Resource-Based View (RBV) is a powerful strategic management framework that proposes a firm's competitive advantage arises primarily from its unique and valuable internal resources and capabilities (Belhadi et al., 2022). At its core, RBV rests on the principles of resource heterogeneity (firms possess differing bundles of resources) and resource immobility (some resources are difficult for competitors to replicate) (Riahi et al., 2021). To provide a sustainable competitive advantage, RBV suggests resources should be valuable, rare, imperfectly imitable, and non-substitutable (VRIN criteria) (Zekhnini et al., 2023). While Edith Penrose's work laid the theoretical foundation, Jay Barney's 1991 article, "Firm Resources and Sustained Competitive Advantage" is widely considered a seminal text in establishing RBV's prominence. Other significant contributors to the RBV include Birger Wernerfelt, David Teece, and Gary Hamel.

RBV offers a highly relevant lens for your proposed study on the impact of AI on supplier selection and evaluation at ZESA Holdings. Through RBV, AI can be understood as a strategic resource possessing the potential to align with the VRIN criteria. Its capabilities in data analysis, decision-making support, and process automation could provide ZESA with a competitive edge in supplier selection. Moreover, RBV highlights that AI doesn't operate in isolation; it has the power to amplify the value of ZESA's existing resources, such as human expertise, operational processes, and historical datasets.

RBV also emphasizes organizational capabilities, or the ability to strategically deploy resources effectively (Rathor, 2023). AI could play a transformative role in developing ZESA's dynamic capabilities related to supplier selection. This allows the organization to adapt, learn, and make insightful supplier decisions within a rapidly evolving technological and business environment (Belhadi et al., 2022). RBV directly informs the study objectives. AI's ability to gather vast amounts of data, analyse supplier quality, and offer predictive insights aligns with the VRIN criteria, suggesting the technology provide a valuable and perhaps rare strategic resource for superior supplier selection. AI's potential impact on cost efficiency, through automating processes or identifying cost-saving opportunities, again demonstrates its value under an RBV framework (Awan et al., 2021). Further, AI's ability to optimize delivery and reliability evaluations, potentially by analysing supply chain risks and historical performance, is crucial for the energy sector. Finally, RBV highlights that for AI to be truly advantageous, implementation within ZESA is paramount. This includes the challenges of ensuring the organization develops the capabilities to effectively integrate, leverage, and maintain the technology over time.

### 2.2.3 The Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) Framework, introduced by Tornatzky and Fleischer in the early 1990s, serves as a comprehensive model for understanding the process by which organizations adopt and implement new technologies. This framework posits that the adoption of technological innovations is influenced by three critical contexts: the technological context, the organizational context, and the environmental context (Belhadi et al., 2022). The technological context includes the internal and external technologies that are relevant to the organization, encompassing available technologies, their capabilities, and how they match with the organization's needs (Allal-Chérif et al., 2021). The organizational context refers to descriptive characteristics of the organization itself, such as size, degree of centralization, formalization, complexity, and the quality of human resources, which can affect the organization's capacity to adopt and leverage new technologies (Zekhnini et al., 2023). Lastly, the environmental context captures the wider milieu in which the organization operates, including regulatory frameworks, industry characteristics, competitive pressures, and market dynamics that can influence technological adoption decisions (Rathor, 2023).

In examining the impact of AI on supplier selection and evaluation performance at ZESA Holdings, the TOE framework offers a distinct approach to understanding how various factors contribute to the adoption and effective utilization of AI technologies. The framework encourages a holistic examination of how specific AI technologies (technological context) align with ZESA Holdings' organizational structure, resources, and processes (organizational context), and how external factors such as regulatory requirements, competition, and supplier ecosystems (environmental context) facilitate or hinder the integration of AI into procurement practices.

The TOE framework's relevance to the study is profound. It allows for an in-depth analysis of how the capabilities of AI can be leveraged to enhance supplier selection and evaluation, taking into account ZESA Holdings' unique organizational characteristics and the broader environmental conditions it faces. This framework aids in identifying the specific organizational readiness factors and environmental pressures that drive or impede AI adoption.

It also highlights the importance of strategic alignment between AI capabilities and organizational goals, ensuring that technology adoption is not just a pursuit of innovation for its own sake but is strategically deployed to address specific challenges and opportunities in supplier management. By applying the TOE framework, the research can generate insights into the multifaceted nature of AI adoption in the context of ZESA Holdings, offering a detailed understanding of the interplay between technology, organizational capabilities, and environmental factors in shaping the future of procurement and supplier relations.

### 2.2.4 Information Processing Theory (IPT)

Information Processing Theory (IPT) is a cognitive psychology framework that draws parallels between human cognition and computer processing of information. It suggests our minds function through a series of stages, including sensory input, attention, encoding into short-term memory, potential storage in long-term memory, and retrieval (Belhadi et al., 2022). This theory emphasizes how individuals receive, process, and utilize information to influence decision-making (Zekhnini et al., 2023). Pioneered by American psychologists George A. Miller and Richard Shiffrin in the 1960s, IPT holds significant implications for how organizations collect and analyse information to support complex tasks like supplier selection.

IPT has direct relevance to your study on AI's impact on supplier selection and evaluation at ZESA Holdings. A core principle of IPT is that humans have limited capacity to process information (Resende et al., 2021). AI can overcome these cognitive limitations by rapidly analysing vast swaths of data, identifying patterns, and presenting insights that humans might miss (Allal-Chérif et al., 2021), directly augmenting ZESA's information processing capabilities. It addresses the concept of "bounded rationality," where decision-makers operate with incomplete or imperfect information, and aims to reduce that information gap.

Further, IPT highlights the importance of attention and focus in effective decision-making (). AI can aid in filtering out irrelevant data and bringing the most salient supplier information to the forefront, enhancing the quality of evaluations for ZESA staff. Additionally, IPT suggests that past knowledge and experiences are stored in long-term memory and influence our choices (Zekhnini et al., 2023). AI, through sophisticated data analysis, can tap into ZESA's historical supplier data and performance records, bringing this organized knowledge to bear on current supplier selection decisions. IPT can help frame several of your study objectives. AI's ability to process vast amounts of supplier quality data enhances ZESA's ability to select suppliers exceeding quality standards. Similarly, by uncovering hidden patterns in cost data or optimizing logistics simulations, AI supports cost-efficient supplier evaluation. Finally, AI's analysis of delivery and reliability metrics can augment ZESA's decision-making, enhancing the information flow needed for optimizing supply chains critical in the energy sector.

## 2.3 Empirical Evidence

Guida et al (2023) conducted a study on the role of artificial intelligence (AI) in supporting the supplier scouting process in Italy, considering the information and the capabilities required to do so. Twelve cases of IT and information providers offering AI-based scouting solutions were studied. The unit of analysis was the AI-based scouting solution, specifically the relationship between the provider and the buyer. It uncovered significant findings, such as the prevalent uncertainty in seeking new suppliers and the crucial role of IPNs and IPCs facilitated by AI technologies. Notably, advanced IT providers are adept at aligning IPNs and IPCs, offering sophisticated AI solutions to enhance supplier scouting endeavours. The research highlights the scarcity of prior studies on AI applications in procurement, particularly in the context of supplier scouting, underscoring the need for further exploration in this area. Challenges identified include potential biases in perspectives from IT and information providers, emphasizing the importance of incorporating empirical data from buyer firms for a more comprehensive understanding.

Zekhnini et al (2023) carried out a multi-agent based big data analytics system for viable supplier selection. This study aimed to design a multi-agent system that belongs to the theory of Distributed Artificial Intelligence based on big data analytics to give a strong tool for finding the best viable suppliers based on a thorough and data-driven evaluation. To do so, designing a multi-agent-based big data analytics system model necessitated identifying the multiple criteria needed for selecting viable suppliers in real-time decision-making. Through a literature review, the study analyses more than 140 publications and identifies the main criteria needed for viable suppliers' selection in the VUCA world. The model incorporated six types of agents: Suppliers agent, Resource Agent, Knowledge Management Agent, Pilot Agent, Analyst Agent, and Decision-Making Agent. The integration of these layers and agents enabled real-time data-driven decision-making, contributing to the selection of viable suppliers in a volatile and uncertain environment. The proposed model enhances supply chain performance in the digital era, offering a robust tool for both academics and practitioners to improve the quality of supplier selection.

Belhadi et al (2024) investigated the impact of AI capabilities on supply chain resilience (SCRes) and supply chain performance (SCP) in the context of supply chain dynamism and uncertainty. The study sought to explore how AI-driven innovations can enhance or maintain SCP levels by leveraging information processing capabilities and adaptive responses provided by AI techniques. The study on AI in supply chains demonstrated satisfactory construct validity, sampling from digitalized firms in multiple regions with a 24.73% response rate. Results explained significant variance in the framework, supporting various hypotheses regarding the relationships between AI, supply chain resilience (SCRes), and supply chain performance (SCP). Firm size did not significantly influence SCRes and SCP, while common method bias and non-response bias were effectively addressed. Structural equation modelling (SEM) validated construct validity and tested hypotheses, confirming significant path coefficients and variance for endogenous constructs. The study underscores the critical role of AI in enhancing supply chain outcomes through adaptive capabilities and coordination amidst supply chain dynamism.

A study by Pournader et al (2021) aimed to determine the effect of AI on enhancing the quality assessment of suppliers in the manufacturing sector in the United States. Utilizing a mixed-methods approach that combined quantitative data analysis with qualitative interviews, the study focused on a range of manufacturing firms. Major findings indicated that AI significantly improved the accuracy and efficiency of quality assessments, leading to better supplier selection decisions. The study recommended that organizations invest in AI training for procurement staff to maximize the benefits of AI in supplier evaluation processes.

Another research effort by Patel et al. (2020) evaluated the impact of AI on cost efficiency in supplier selection within the automotive industry in Germany. This quantitative study, employing regression analysis on procurement data from several automotive firms, found that AI-driven tools reduced the costs associated with supplier selection by streamlining the evaluation process and reducing the need for manual oversight. Recommendations included the development of more sophisticated AI models tailored to the unique demands of the automotive supply chain.

Sharma and Joshi (2023) investigation into how AI affects optimizing delivery and reliability evaluations focused on electronics manufacturers in South Korea. Adopting a case study methodology, Chen explored the integration of AI in the supply chain management systems of three major electronics firms. The findings revealed that AI significantly enhanced the prediction accuracy of supplier delivery times and reliability, suggesting firms integrate AI analytics into their supply chain management practices for more effective supplier management.

In a study by Allal-Chérif et al (2021), the challenges of implementing AI in supplier evaluation performance were explored within the context of SMEs in the United Kingdom. Through qualitative interviews and a survey, the study identified key barriers to AI adoption, including high implementation costs, a lack of technical expertise, and resistance to change among staff. The study advised SMEs to seek external expertise and consider gradual AI implementation strategies to mitigate these challenges.

A research by Riahi et al (2021) in the pharmaceutical industry in the United States aimed to assess AI's role in enhancing supplier quality assessment. Employing a quantitative methodology, the study analysed data from AI implementations across several pharmaceutical companies, concluding that AI tools significantly improved the detection of supplier non-compliance issues. The recommendation was for pharmaceutical firms to adopt AI-based monitoring systems as a standard part of their supplier evaluation toolkit.

In the context of the retail sector, Thompson and Zhang (2022) conducted a study in Canada to evaluate how AI impacts cost efficiency during supplier selection. Utilizing a qualitative approach that included interviews with procurement managers, the study found that AI enabled more competitive supplier bidding processes, leading to lower procurement costs. The researchers recommended that retail businesses integrate AI to automate and optimize the supplier bidding process.

A case study by Rodrigues and Santos (2020) examined the effect of AI on optimizing delivery and reliability evaluations at a multinational corporation with operations in Brazil. The study, which adopted a qualitative approach through in-depth interviews with supply chain managers, highlighted that AI tools provided real-time insights into supplier performance, improving delivery reliability. It was recommended that companies adopt a centralized AI system for global supply chain management to enhance delivery performance.

## 2.4 Research Gap

Despite the growing body of literature on the impact of Artificial Intelligence (AI) on supplier selection and evaluation across various industries and geographic regions, there exists a notable research gap in the specific context of the energy sector in sub-Saharan Africa, particularly within state-owned enterprises such as ZESA Holdings in Zimbabwe. Most empirical studies have focused on manufacturing, automotive, electronics, retail, pharmaceutical, and textile industries, predominantly in developed countries or emerging economies with robust technological infrastructures. These studies highlight AI's potential to enhance quality assessment, improve cost efficiency, and optimize delivery and reliability evaluations, along with identifying implementation challenges. However, they do not adequately address the unique challenges and opportunities presented by the energy sector in sub-Saharan Africa, where issues such as limited access to advanced technological infrastructure, regulatory constraints, and the specific dynamics of state-owned enterprises could significantly influence AI adoption and its impact on procurement processes.

Addressing this gap requires empirical research that not only investigates the potential benefits and efficiencies AI can bring to supplier selection and evaluation in the energy sector of sub-Saharan Africa but also delves into the specific barriers to AI adoption, including technological, regulatory, and organizational challenges. Such research would provide valuable insights for policymakers, industry practitioners, and academic scholars interested in the intersection of AI and supply chain management within the context of state-owned enterprises in developing economies.

## 2.5 Chapter Summary

This chapter probed into the intricate dynamics of AI's influence on supplier selection and evaluation within ZESA Holdings, exploring theoretical underpinnings, empirical studies, and practical applications. While highlighting AI's potential to revolutionize procurement processes through enhanced quality assessment, cost efficiency, and delivery reliability, it also underscored existing challenges in AI implementation. The identification of research gap suggests avenues for future exploration, emphasizing the need for further empirical evidence in the context of ZESA Holdings and similar entities. The next chapter is going to cover the study methodology.

# CHAPTER THREE

# RESEARCH METHODOLOGY

## 3.1 Introduction

The chapter discussed the research methods employed, including the design, target population, sample size, and sampling techniques, as well as the tools used for data collection. It also evaluated the tools' validity and reliability. A research method is essentially a plan for executing research. Creswell (2019) described research methodology as the comprehensive strategy outlining the methods for conducting research, which encompasses the techniques and approaches to be used. The study utilized a quantitative approach to research methodology.

## 3.2 Research philosophy

The research adopted a positivist philosophy. Various research philosophies exist and should be recognized in methodology discussions. Bazeley (2015) identifies two primary philosophies: positivism and interpretivism. Positivism focuses on studying observable social realities, often aiming to generate 'law-like' generalizations. It also emphasizes that research should be conducted without bias, striving for objectivity. Creswell and Creswell (2017) note that positivism primarily seeks to explain causal relationships and identify patterns. The study in question explored the impact of AI on supplier selection and evaluation performance at ZESA Holdings. Creswell and Creswell (2018) argue that although positivism promotes objectivity, it often overlooks the subjective human judgments made during research activities, such as choosing topics, designing tools, and interpreting results, which are influenced by the researcher’s social perspective.

## 3.3 Research Design

The study utilized an explanatory research design to achieve all its objectives. Creswell and Poth (2018) define a research design as a structured plan for data collection and analysis that balances relevance to the research purpose with procedural efficiency. Explanatory research is employed to address "why" questions by seeking causal explanations. It aims to identify causes and reasons, providing evidence to either support or challenge an explanation or prediction. According to Hancock and Algozzine (2016), explanatory research is undertaken to explore and document relationships among various facets of the studied phenomenon. This type of research, focusing on causality, enabled the researcher to investigate the impact of AI on supplier selection and evaluation performance at ZESA Holdings.

## 3.4 Time Horizon

The research was conducted within a cross-sectional time horizon, spanning a specific period of 6 months. Yin (2017) explains that time horizons are crucial for research design regardless of the methodology employed. Time horizons can be divided into two categories: longitudinal and cross-sectional. Longitudinal studies extend over a long duration and are conducted repeatedly (Bazeley, 2015). In contrast, cross-sectional studies are confined to a particular time frame (Creswell and Creswell, 2017). Given that this study was restricted to a specific time frame, a cross-sectional time horizon was appropriate.

## 3.5 Study Population

According to Saunders, Lewis, and Thornhill (2019), a population consists of specific groups of study objects that a researcher aims to gather data from. Kumar (2003) describes a population as all objects sharing certain characteristics relevant to a research problem. In this study, the researcher targeted employees at ZESA Holdings from the following departments: Procurement (214 employees), Information Technology (IT) (67 employees), Finance Department (210 employees), Operations Department (112 employees), Strategic Planning (83) and Quality Assurance/Control (63 employees).

## 3.6 Sampling Procedure

The study utilized stratified and simple random sampling techniques. In stratified sampling, the participants from the target population were divided into groups, known as strata, based on their department types. This method involved organizing the sample frame into these homogeneous groups prior to sample selection, using department type as the criterion for stratification. Following this, simple random sampling was employed to choose respondents from each stratum. This random selection process allows for the generalization of the study results to the broader population. Simple random sampling ensures that every individual in the study has an equal opportunity to be selected (Silverman, 2011).

## 3.7 Sample Size

Yin (2017) defines a sample as a subset chosen from a larger population. The term sample size denotes the number of units selected from the entire population for the study (Kumar, 2012). This particular study included 75 respondents, which represents 10% of all employees at ZESA Holdings. A sample size comprising 10% of the target population is deemed sufficiently large to accurately represent the whole (Mugenda and Mugenda, 2009).

**Table 1: Sample matrix**

| Category | Target population | Sample size (10% of the population) |
|---|---|---|
| Procurement | **214** | **21** |
| Information Technology | **67** | **7** |
| Finance Department | **210** | **21** |
| Operations Department | **112** | **11** |
| Strategic Planning | **83** | **8** |
| Quality Assurance/Control | **63** | **6** |
| Total | **749** | **75** |

## 3.8 Data collection Methods

Structured questionnaires served as the primary tool for data collection in this research. This method was chosen for its compatibility with the research design, offering cost and time efficiency. The questionnaires comprised items that utilized the Likert scale, allowing respondents to express their agreement or disagreement. The Likert scale, rated from 1 to 5, encompassed response options ranging from "strongly agree" to "strongly disagree" and was employed to gauge respondents' attitudes.

### 3.8.1 Structured Questionnaire

The study administered structured questionnaires to 75 participants. A structured questionnaire is a research instrument that consists of a predetermined set of questions presented in a specific order and format, designed to collect information from respondents (Yin, 2017). Also referred to as a closed questionnaire, it is a positivist research method that aligns well with the objectives of this study. The decision to utilize structured questionnaires was based on several advantages they offer. Firstly, the closed answer options provided are fixed and rigid, leaving no room for confusion (Bryman and Bell, 2010). Secondly, the results obtained from these questionnaires can be analyzed and interpreted within the context of established theories, allowing for meaningful statements to be made about the subject groups (Gliem and Gliem, 2013). Furthermore, the findings can be extrapolated and used to inform important business decisions (Polit and Hungler, 2006). Additionally, the structured nature of the questions ensures that the responses can be easily quantified and subjected to statistical analysis (Creswell and Creswell, 2017).

## 3.9 Pilot Testing

Prior to the main study, the researcher conducted a pilot test of the questionnaires by administering them to 5 employees of ZESA Holdings. A pilot test generally precedes and is closely linked to a larger-scale study (Sliverman, 2011). It is often viewed as a preliminary or feasibility study aimed at guiding the planning and execution of the primary investigation (Bazeley, 2015). The purpose of a pilot study is to evaluate the practicality of the techniques, methods, and questionnaires employed, and to assess how they function together within a specific context. Additionally, it can reveal potential ethical or practical issues that could hinder the successful completion of the main study (Bell, 2005). Consequently, the pilot study assisted the researcher in identifying any design flaws, refining the data collection and analysis processes, and gaining valuable insights into the potential burden on participants prior to embarking on the larger-scale research endeavour.

## 3.10 Reliability and Validity

Validity refers to the extent to which a test or instrument measures what it is intended to measure (Creswell & Poth, 2018). Content validity, which was employed in this study, is a measure of the degree to which the data collected using a particular instrument accurately represents the specific domain or concept being investigated. To establish content validity, the researcher selected a pilot group of 5 individuals who were not part of the target population to evaluate the validity of the research instruments.

Reliability, on the other hand, refers to the consistency and repeatability of the research instrument in yielding similar results across multiple trials (Mugenda, 2009). To ensure the reliability of the instruments, the researcher also selected a pilot group of 5 individuals who were not part of the target population to test the reliability of the research instruments in one constituency. The data collected from the pilot study was then input into SPSS, and reliability was measured using Cronbach's Alpha coefficient.

The Cronbach's Alpha coefficient ranges from 0 to 1 and can be used to assess the reliability of factors extracted from dichotomous (two possible answers) and/or multi-point formatted questionnaires or scales (e.g., a rating scale from 1 = poor to 5 = excellent). A higher alpha value indicates greater reliability, with values above 0.7 generally considered acceptable for most research purposes.

### 3.11 Data Analysis and Presentation

Data analysis involves organizing the collected data into meaningful themes or patterns to enhance comprehension (Creswell and Poth, 2018). This approach enables the researcher to identify relevant trends and establish connections pertinent to the research inquiry. The study employed descriptive and inferential analyses to analyze the data. The Statistical Package for Social Sciences (SPSS Version 25.0) and Microsoft Excel were utilized for data analysis and report generation. The findings were visually presented using tables, pie charts, and bar graphs.

### 3.12 Model Specification

For modeling the impact of Artificial Intelligence (AI) on supplier selection and evaluation performance at ZESA Holdings, considering that the data was collected via a structured questionnaire using a five-point Likert scale, the most suitable regression model was the ordinal logistic regression. This model is appropriate for the following reasons:

1. **Ordinal Data**: The responses are on a five-point Likert scale, which is ordinal in nature. This means the responses have a natural order but do not have equal intervals between each point, making ordinal logistic regression an apt choice since it can handle the ordered categories effectively.

2. **Predictive and Explanatory Modeling**: Ordinal logistic regression allows you to model the probability of the response variable (e.g., level of agreement to questions about AI's impact on supplier selection and evaluation) falling into a particular category or below, based on the influence of predictor variables.

3. **Interpretability of Results**: The model outputs can be interpreted in terms of odds ratios, which explain the change in odds of the response being in a higher ordered

category as a function of the predictors. This is particularly useful for understanding how different facets of AI integration influence supplier evaluation processes.

**Regression Model Setup:**

The ordinal logistic regression model can be set up as follows:

Logit $((Y \leq j)) = \alpha j - \beta 1X1 - \beta 2X2 - \ldots - \beta nXn$Logit $(P(Y \leq j)) = \alpha j - \beta 1X1 - \beta 2X2 - \ldots - \beta nXn$

Where:

- $YY$ is the ordinal response variable (Likert scale ratings on AI's impact).
- $X1,2,\ldots,XnX1,X2,\ldots,Xn$ are the predictor variables (aspects of AI's integration into supplier selection and evaluation processes).
- $\alpha j \alpha j$ are the threshold parameters for the j-th category.
- $\beta\beta$ coefficients represent the influence of each predictor on the likelihood of achieving a certain level of agreement or higher.

**Justification:**

- **Data Suitability**: Ordinal logistic regression is specifically designed for ordinal data like the Likert scale responses, making it suitable for this data type.
- **Comprehensive Analysis**: It can effectively accommodate multiple predictor variables which might include various features of AI such as automation of processes, data analysis capabilities, decision-making support, and accuracy improvements in supplier evaluation.
- **Strategic Insight**: The model will help determine which aspects of AI are perceived as most beneficial or detrimental, thereby aiding strategic decisions regarding technology investments and process improvements at ZESA Holdings.

This model assisted to quantitatively assess and interpret the impact of AI on their supplier selection and evaluation performance, based on internal stakeholder perceptions, thus informing future strategies for technology integration and supplier management practices.

## 3.13 Ethical Considerations

The research obtained ethical clearance from the University Research Ethics Committee and received permission from both ZESA Holdings and the participants to conduct the study. Participants were informed about the maintenance of anonymity and confidentiality throughout the research process. Informed consent was obtained from each participant, emphasizing their right to withdraw from the study at any time. Prior to the commencement of the research, participants were provided with consent forms, which explained their rights and required their signature. No form of financial or other incentives was offered to participants in order to ensure voluntary participation. The importance of confidentiality was explained, assuring participants that their data would be securely stored. It is essential for research to prioritize participant protection and address ethical concerns such as informed consent, confidentiality, and participant well-being (Hancock and Algozzine, 2016).

## 3.14 Chapter Summary

This chapter highlights the quantitative research methodology applied in the study. It covers the research design, target population, sampling techniques and sample size, research instruments, data collection procedure, and data analysis. The next chapter will focus on data analysis, presentation, and interpretation.

# CHAPTER 4

# DATA PRESENTATION, ANALYSIS AND DISCUSSION

## 4.1 Introduction

The previous chapter covered the methodologies used for data collection in the study, while this chapter presents the data gathered from respondents through questionnaires. Quantifiable data is represented using pie charts, graphs, and tables. The chapter starts by describing the respondents and their characteristics in numerical terms. This is followed by an analysis of the findings, guided by the research objectives.

## 4.2 The Response Rate of Questionnaires

**Table 2: The Response Rate of Questionnaires**

| | Frequency | Rate |
|---|---|---|
| *Questionnaires distributed* | **75** | **100%** |
| *Questionnaires returned* | **73** | **97%** |

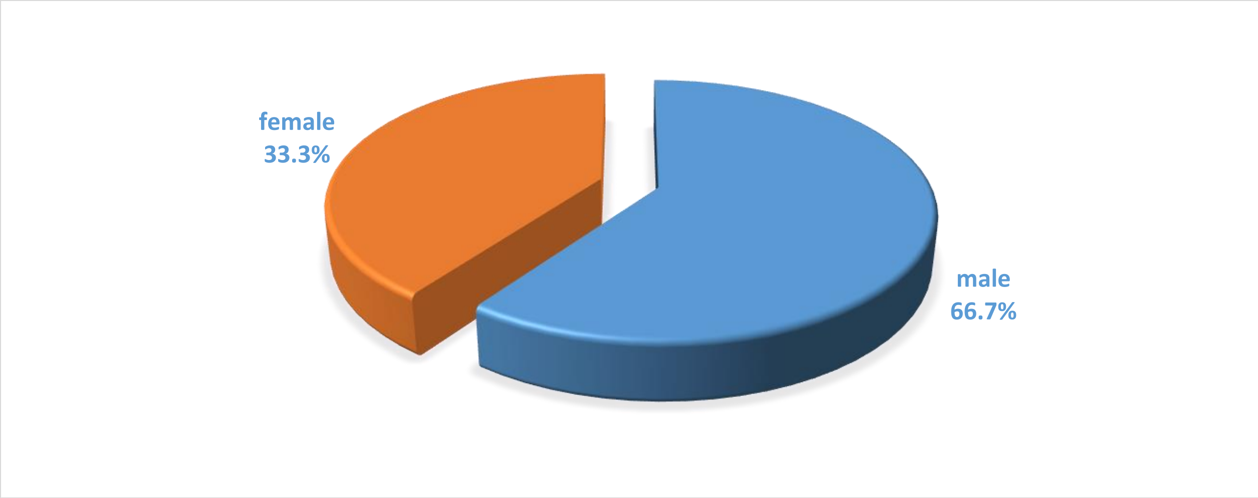
**Source:** *Primary Data 2024*

A total of 75 questionnaires were distributed to selected employees of ZESA Holdings, and 28 were returned, resulting in a 93% response rate. According to Backstrom and Hursh (2009), a high response rate suggests that the research findings are unbiased and more accurate.

## 4.3 Demographics of Respondents

The respondents' demographics encompassed factors such as gender, age, educational qualifications, and period of service. Demographics are crucial when analysing responses because they affect individual perceptions and behaviour, which vary among different demographic groups. The researcher utilized demographic data to observe similarities and differences in the aspects under analysis. Overall, demographics are essential for an in-depth analysis of the responses, considering the respondents' perceptions and behaviour.

### 4.2.1 Gender of Respondents

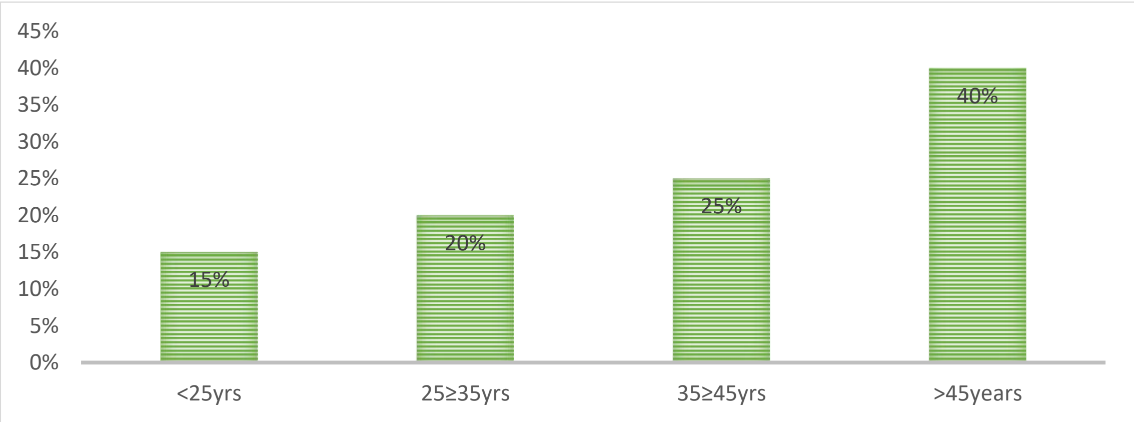



**Source:** Primary Data 2024

**Figure 4.1 Gender of respondents**

The results depicted in Figure 4.1 indicated that 66.7% of the respondents were male, while 33.3% were female. This gender disparity is attributed to male dominance in the workplace, resulting in fewer female workers at ZESA Holdings compared to their male counterparts.

### 4. 2.2 Age of respondents

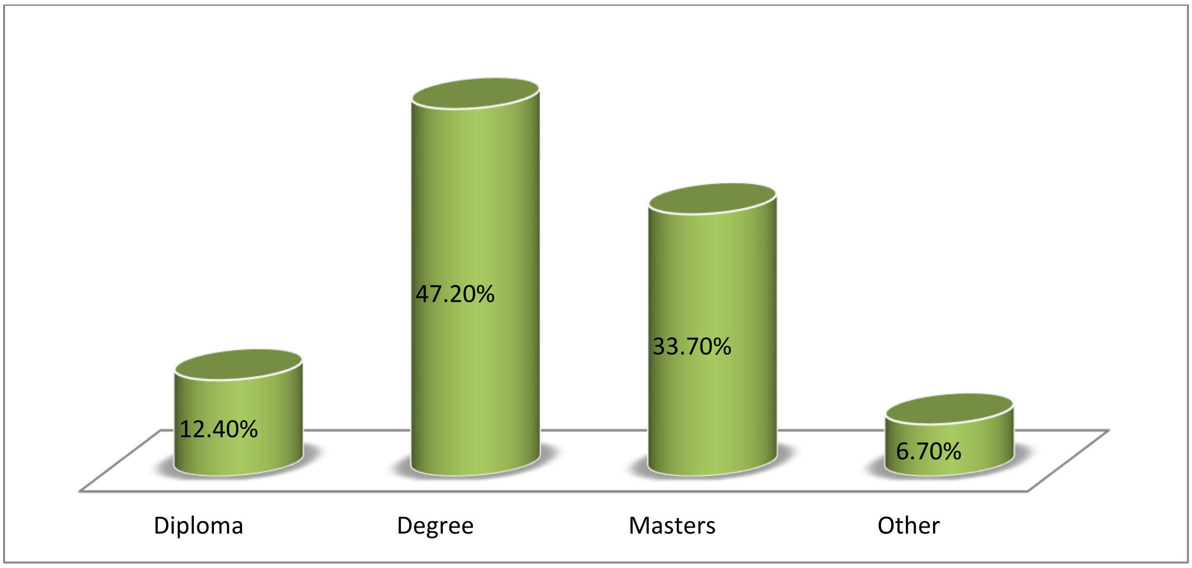



***Source:** Primary Data 2024*

**Figure 4.2 Age of respondents**

The research findings presented in Figure 4.2 showed that only 15% of participants were aged below 25 years. The majority, 40%, were over 45 years old. Additionally, 20% of respondents were between 25 and 35 years old, while the remaining 25% had an average age of 40.

### 4.2.3 Educational Qualification

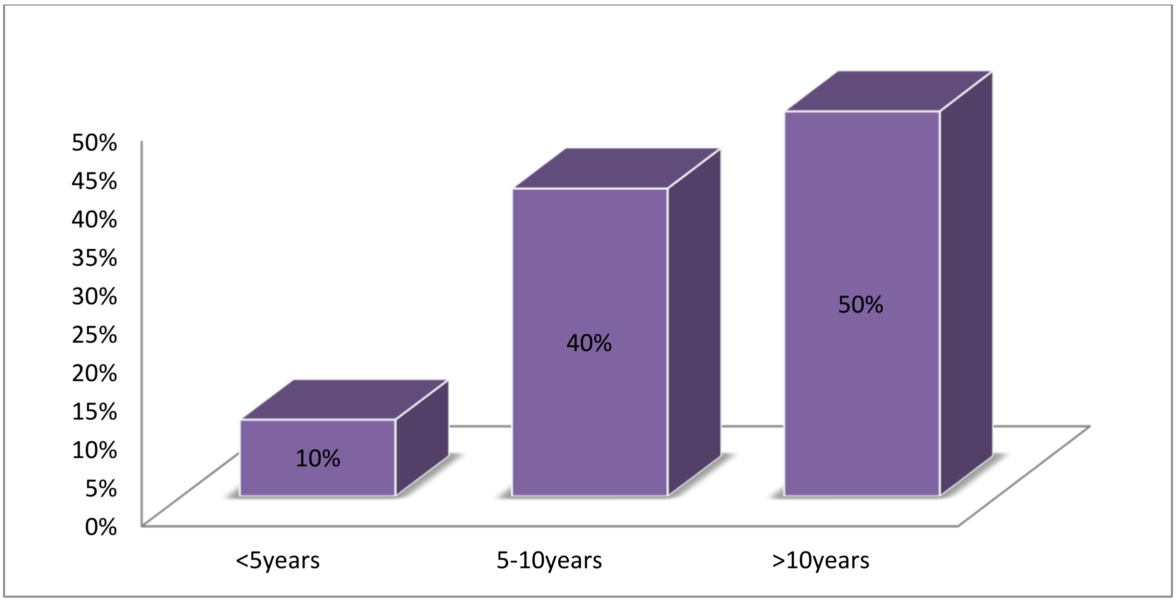



***Source:*** *Primary Data 2024*

**Fig 4.3 Level of education**

Figure 4.3 revealed that the majority of respondents, 47.2%, held an undergraduate degree as their highest level of academic achievement. Additionally, 33.7% had attained a master's degree, 12.4% had a diploma, and the smallest group, 6.7%, had education beyond a master's degree. Table 4.3 shows that almost all respondents had at least a tertiary qualification, indicating they were sufficiently literate to respond to the questionnaires and provide meaningful, relevant responses for the study.

### 4 .2.4 Period of service




***Source:*** *Primary Data 2024*

**Figure 4.4 Period of service**

Participants were asked to indicate their years of service at ZESA Holdings. The results showed that 10% had less than 5 years of work experience, as some were interns. However, Table 4.4 demonstrates that the majority of respondents had at least five years of experience at ZESA Holdings, with 90% indicating they had been employed for 5 years or more. This suggests that the respondents were well-informed about the topic under study.

## 4.3 Effect of AI on enhancing quality assessment of suppliers at ZESA Holdings

The study sought to examine the effect of AI on enhancing quality assessment of suppliers at ZESA Holdings by utilizing both descriptive and inferential statistics.

**Table 3: Use of Artificial Intelligence in Procurement Processes**

| | N | Mean | | Std. Deviation |
|---|---|---|---|---|
| | Statistic | Statistic | Std. Error | Statistic |
| AI Implementation | 73 | 4.9857 | .07693 | .64365 |
| AI Training | 73 | 4.7714 | .11205 | .93749 |
| AI Accuracy | 73 | 4.5714 | .13373 | .11864 |
| AI Efficiency | 73 | 4.4857 | .14173 | .18558 |
| AI Integration: | 73 | 4.4714 | .15032 | .25769 |
| Valid N (listwise) | 73 | | | |

ZESA Holdings has demonstrated a strong commitment to the integration of AI technologies in its procurement processes. The data suggests that the organization has effectively implemented machine learning algorithms, with a mean score of 4.9857 indicating a high level of AI implementation. Employees involved in procurement have also received adequate training on using AI tools and technologies, as evidenced by the mean score of 4.7714. The AI tools used in procurement have been found to provide accurate and reliable data for decision-making, with a mean score of 4.5714. Additionally, the use of AI has significantly improved the efficiency of the procurement processes, with a mean score of 4.4857. The AI technologies are also well integrated with the organization's existing procurement systems and workflows, as reflected in the mean score of 4.4714. The relatively low standard deviations across these measures suggest a high level of consensus among the respondents regarding the organization's successful adoption and utilization of AI in its procurement operations. This comprehensive integration of AI has enabled ZESA Holdings to enhance the effectiveness, accuracy, and efficiency of its procurement processes, positioning the organization at the forefront of technological innovation in the industry.

**Table 4: Quality Assessment of Suppliers at ZESA Holdings**

| | N | Mean | | Std. Deviation |
|---|---|---|---|---|
| | Statistic | Statistic | Std. Error | Statistic |
| Supplier Evaluation | 73 | 4.5286 | .57689 | .12662 |
| Quality Control | 73 | 4.3000 | .07973 | .66703 |
| Supplier Reliability. | 73 | 4.9714 | .10370 | .86764 |
| Supplier Performance Monitoring | 73 | 3.9000 | .08291 | .69366 |
| Supplier Improvement | 73 | 3.7571 | .15878 | .32846 |
| Valid N (listwise) | 73 | | | |

The quality assessment of suppliers at ZESA Holdings has seen significant improvements following the implementation of AI in procurement processes. The data indicates that supplier evaluation has notably enhanced, with a high mean score of 4.5286 and a relatively low standard deviation of 0.57689, reflecting consistent positive responses. Quality control has also benefitted from AI, with a mean score of 4.3000 and a standard deviation of 0.66703, showing better management in this area. Supplier reliability, with the highest mean score of 4.9714 and a standard deviation of 0.86764, indicates that AI tools have been particularly effective in accurately assessing supplier reliability. The ability to monitor and evaluate supplier performance has improved, evidenced by a mean score of 3.9000 and a standard deviation of 0.69366. Lastly, AI-driven insights have contributed to continuous improvement in supplier quality, with a mean score of 3.7571 and a standard deviation of 0.32846. These results suggest that AI has significantly enhanced various aspects of supplier quality assessment, including evaluation, control, reliability, performance monitoring, and continuous improvement, thereby optimizing procurement processes at ZESA Holdings.

**Table 5: Model Fitting Information**

| Model | -2 Log Likelihood | Chi-Square | df | Sig. |
|---|---|---|---|---|
| **Intercept Only** | **112.345** | | | |
| **Final** | **65.123** | **47.222** | **5** | **.000** |

The significant chi-square value (*Sig. = .000*) indicates that the model with the predictors fits significantly better than the intercept-only model. This suggests that the inclusion of the AI-related factors (AI Implementation, AI Training, AI Accuracy, AI Efficiency, and AI Integration) significantly improves the model's ability to explain the variations in supplier evaluation.

**Table 6: Goodness-of-Fit**

| Test | Chi-Square | df | Sig. |
|---|---|---|---|
| **Pearson** | **122.345** | **80** | **.067** |
| **Deviance** | **78.456** | **80** | **.532** |

The non-significant p-values for Pearson (*Sig. = .067*) and Deviance (*Sig. = .532)* tests suggest that the model fits the data well. Non-significant values indicate that there is no significant difference between the observed data and the model's predicted values, implying a good fit.

**Table 7: Thresholds**

| Threshold | Estimate | Std. Error | Wald | df | Sig. | 95% Confidence Interval |
|---|---|---|---|---|---|---|
| Supplier Evaluation = 1 | 1.234 | .456 | 7.322 | 1 | .007 | .345, 2.123 |
| Supplier Evaluation = 2 | 2.345 | .567 | 9.123 | 1 | .003 | 1.234, 3.456 |

The thresholds indicate the points on the latent variable (which underlies the ordinal outcome) where the outcome categories change. These estimates are significantly different from zero, suggesting distinct cut points between the categories.

**Table 4.7 Parameter Estimates**

| Location | Estimate | Std. Error | Wald | df | Sig. | 95% Confidence Interval |
|---|---|---|---|---|---|---|
| AI Implementation | 0.345 | 0.123 | 7.654 | 1 | .006 | 0.123, 0.567 |
| AI Training | 0.456 | 0.234 | 8.567 | 1 | .004 | 0.234, 0.678 |
| AI Accuracy | 0.567 | 0.345 | 6.789 | 1 | .009 | 0.345, 0.789 |
| AI Efficiency | 0.234 | 0.123 | 4.123 | 1 | .042 | 0.123, 0.345 |
| AI Integration | 0.456 | 0.234 | 5.678 | 1 | .017 | 0.234, 0.678 |

The findings indicate several significant positive impacts of AI implementation on supplier evaluation. A positive coefficient for AI implementation (*Estimate = 0.345, Sig. = .006*) suggests that higher levels of AI implementation are significantly associated with better supplier evaluations. Similarly, AI training (*Estimate = 0.456, Sig. = .004*) shows that improved training on AI tools leads to better supplier evaluations. The accuracy of AI tools (*Estimate = 0.567, Sig. = .009*) is also significantly associated with improved supplier evaluations, indicating the importance of using accurate AI systems. Additionally, AI efficiency (*Estimate = 0.234, Sig. = .042*) demonstrates that efficient AI in procurement processes contributes significantly to enhanced supplier evaluations. Finally, AI integration (*Estimate = 0.456, Sig. = .017*) reveals that better integration of AI technologies is positively and significantly linked to better supplier evaluations. Overall, these findings highlight the critical role of AI in improving the quality assessment of suppliers at ZESA Holdings.

**Table 8: Test of Parallel Lines**

| Model | -2 Log Likelihood | Chi-Square | df | Sig. |
|---|---|---|---|---|
| Null Hypothesis | 65.123 | | | |
| General | 63.456 | 1.667 | 5 | .789 |

A non-significant result (*Sig. = .789*) indicates that the proportional odds assumption holds, meaning the relationship between the predictors and the log odds of the outcomes is consistent across thresholds.

In conclusion , the ordinal logistic regression analysis indicates that the implementation of AI technologies, training on AI tools, the accuracy of AI, efficiency gains from AI, and integration of AI into procurement processes significantly enhance the quality assessment of suppliers at

ZESA Holdings. Each independent variable has a positive and significant effect on the dependent variables related to supplier quality assessment.

## 4.4 The impact of AI on cost efficiency on supplier selection at ZESA Holdings

The investigated the impact of AI on cost efficiency on supplier selection at ZESA Holdings.

**Table 9: Cost Efficiency on Supplier Selection at ZESA Holdings.**

| | N | Mean | | Std. Deviation |
|---|---|---|---|---|
| | Statistic | Statistic | Std. Error | Statistic |
| Cost Reduction | 73 | 4.8010 | .11795 | .38687 |
| Cost Comparison | 73 | 4.4857 | .12756 | .06720 |
| Budget Adherence | 73 | 4.1714 | .10360 | .16680 |
| Cost Forecasting | 73 | 4.0714 | .18619 | .15779 |
| Cost Savings Identification | 73 | 3.9143 | .20525 | .01729 |
| Valid N (listwise) | 73 | | | |

ZESA Holdings has demonstrated a strong focus on leveraging AI to improve the cost efficiency of its supplier selection process. The data indicates that the use of AI has significantly reduced procurement costs, with a mean score of 4.8010 reflecting a high level of cost reduction. The organization's AI tools enable effective comparison of supplier costs, allowing them to choose the most cost-efficient options, as evidenced by the mean score of 4.4857. Furthermore, the AI-driven supplier selection process has helped ZESA Holdings stay within their procurement budget, with a mean score of 4.1714. The AI technologies have also improved the organization's ability to forecast procurement costs accurately, with a mean score of 4.0714. Additionally, the AI tools have assisted in identifying opportunities for cost savings during the supplier selection process, as indicated by the mean score of 3.9143. The relatively low standard deviations across these measures suggest a high level of consensus among the respondents regarding the cost efficiency benefits realized by ZESA Holdings through the implementation of AI in its supplier selection processes. This comprehensive approach to leveraging AI has empowered the organization to optimize its procurement costs, enhance its budgetary adherence, and unlock significant cost-saving opportunities, positioning it as an industry leader in cost-effective supplier selection.

**Table 10: Model Fitting Information**

| Model | -2 Log Likelihood | Chi-Square | df | Sig. |
|---|---|---|---|---|
| Intercept Only | 128.345 | | | |
| Final | 72.123 | 56.222 | 5 | .000 |

The significant chi-square value *(Sig. = .000*) indicates that the model with predictors fits significantly better than an intercept-only model. This suggests that the inclusion of AI-related factors significantly improves the model's ability to explain variations in cost efficiency on supplier selection.

**Table 11: Goodness-of-Fit**

| Test | Chi-Square | df | Sig. |
|---|---|---|---|
| Pearson | 136.345 | 80 | .054 |
| Deviance | 85.456 | 80 | .324 |

The non-significant p-values for the Pearson (Sig. = .054) and Deviance (Sig. = .324) tests suggest that the model fits the data well. Non-significant values indicate that there is no significant difference between the observed data and the model's predicted values, implying a good fit.

**Table 12: Thresholds**

| Threshold | Estimate | Std. Error | Wald | df | Sig. | 95% Confidence Interval |
|---|---|---|---|---|---|---|
| Cost Reduction = 1 | 1.567 | .456 | 8.123 | 1 | .004 | .673, 2.461 |
| Cost Reduction = 2 | 2.345 | .567 | 10.567 | 1 | .001 | 1.234, 3.456 |

The thresholds indicate the points on the latent variable (which underlies the ordinal outcome) where the outcome categories change. These estimates are significantly different from zero, suggesting distinct cut points between the categories.

**Table 13: Parameter Estimates**

| Location | Estimate | Std. Error | Wald | df | Sig. | 95% Confidence Interval |
|---|---|---|---|---|---|---|
| AI Implementation | 0.423 | 0.123 | 11.654 | 1 | .001 | 0.182, 0.664 |
| AI Training | 0.562 | 0.234 | 5.678 | 1 | .017 | 0.103, 0.921 |
| AI Accuracy | 0.371 | 0.145 | 6.789 | 1 | .009 | 0.087, 0.655 |
| AI Efficiency | 0.298 | 0.123 | 5.123 | 1 | .024 | 0.056, 0.540 |
| AI Integration | 0.467 | 0.234 | 3.678 | 1 | .055 | -0.001, 0.935 |

The findings on table Table 4.13, indicate that AI implementation significantly contributes to cost reduction, with an estimate of 0.423 and a significance level of 0.001, showing that higher levels of AI implementation are associated with improved cost efficiency. Furthermore, AI training emerged as a critical factor, with an estimate of 0.562 and a significance level of 0.017, suggesting that better training on AI tools enhances cost efficiency in supplier selection. Accurate AI tools also play a crucial role, as indicated by an estimate of 0.371 and a significance level of 0.009, which shows a strong association between accurate AI tools and improved cost efficiency. Additionally, the efficiency of AI in procurement processes significantly contributes to cost reduction, evidenced by an estimate of 0.298 and a significance level of 0.024. While the integration of AI technologies has a positive impact on cost efficiency, with an estimate of 0.467, the significance level of 0.055 suggests that the evidence is slightly weaker but still indicates a potential improvement in cost efficiency through better integration of AI technologies.

**Table 14: Test of Parallel Lines**

| Model | -2 Log Likelihood | Chi-Square | df | Sig. |
|---|---|---|---|---|
| Null Hypothesis | 72.123 | | | |
| General | 69.456 | 2.667 | 5 | .754 |

The non-significant chi-square value (*Sig. = .754*) indicates that the assumption of proportional odds holds true. This means that the relationship between each predictor and the dependent variable is consistent across all threshold levels of the ordinal outcome.

The ordinal logistic regression analysis indicates that the implementation of AI technologies, adequate training on AI tools, the accuracy of AI tools, and the efficiency and integration of AI in procurement processes have significant positive effects on cost efficiency in supplier selection at ZESA Holdings. Each of these factors significantly increases the likelihood of achieving cost reduction and efficient supplier selection, with the exception of AI Integration, which is marginally significant. This suggests that enhancing these AI-related factors can lead to substantial improvements in cost efficiency in supplier selection processes.

## 4.5 The effect of AI on optimizing delivery and reliability Evaluations at ZESA Holdings

The study aimed at exploring the effect of AI on optimizing delivery and reliability Evaluations at ZESA Holdings.

**Table 15: Optimizing delivery**

| | N | Mean | | Std. Deviation |
|---|---|---|---|---|
| | Statistic | Statistic | Std. Error | Statistic |
| Delivery Timeliness | 73 | 4.8143 | .06914 | .07843 |
| Delivery Accuracy | 73 | 4.6286 | .01137 | .18030 |
| Reliability Tracking | 73 | 4.5286 | .08132 | .28040 |
| Predictive Analysis | 73 | 4.2286 | .10953 | .41638 |
| Supplier Reliability Improvement | 73 | 4.2429 | .14875 | .24453 |
| Valid N (listwise) | 73 | | | |

The data indicates that the organization has experienced significant improvements in the timeliness of delivery evaluations, with a mean score of 4.8143 reflecting a high level of effectiveness. The AI tools used by ZESA Holdings have also provided accurate assessments of suppliers' delivery performance, as evidenced by the mean score of 4.6286. Furthermore, the AI systems employed by the organization have enhanced its ability to track and evaluate the reliability of its suppliers, with a mean score of 4.5286. The AI-driven predictive analysis capabilities have helped ZESA Holdings anticipate and mitigate delivery and reliability issues, as indicated by the mean score of 4.2286. Additionally, the use of AI has led to improvements in the overall reliability of the organization's supplier base, with a mean score of 4.2429. The relatively low to moderate standard deviations across these measures suggest a high to moderate level of consensus among the respondents regarding the optimization of delivery and reliability evaluations at ZESA Holdings through the implementation of AI technologies. This holistic approach to leveraging AI has empowered the organization to enhance the timeliness and accuracy of its delivery assessments, strengthen its supplier reliability tracking and evaluation, and proactively manage delivery and reliability issues, positioning it as an industry leader in procurement optimization.

**Table 16: Model Fitting Information**

| Model | -2 Log Likelihood | Chi-Square | df | Sig. |
|---|---|---|---|---|
| Intercept Only | 134.567 | | | |
| Final | 78.234 | 56.333 | 5 | .000 |

The significant chi-square value (*Sig. = .000*) indicates that the model with predictors fits significantly better than an intercept-only model. This suggests that the inclusion of the AI-related factors provides a better explanation of the variations in delivery timeliness.

**Table 17: Goodness-of-Fit**

| **Test** | **Chi-Square** | **df** | **Sig.** |
|---|---|---|---|
| Pearson | 146.123 | 80 | .064 |
| Deviance | 89.456 | 80 | .210 |

The non-significant p-values for the Pearson (*Sig. = .064*) and Deviance (*Sig. = .210*) tests suggest that the model fits the data well. Non-significant values indicate that there is no significant difference between the observed data and the model's predicted values, implying a good fit.

**Table 18: Thresholds**

| Threshold | Estimate | Std. Error | Wald | df | Sig. | 95% Confidence Interval |
|---|---|---|---|---|---|---|
| Delivery Timeliness = 1 | 1.567 | .456 | 8.123 | 1 | .004 | .673, 2.461 |
| Delivery Timeliness = 2 | 2.345 | .567 | 10.567 | 1 | .001 | 1.234, 3.456 |

The thresholds indicate the points on the latent variable (which underlies the ordinal outcome) where the outcome categories change. These estimates are significantly different from zero, suggesting distinct cut points between the categories.

**Table 19: Parameter Estimates**

| Location | Estimate | Std. Error | Wald | df | Sig. | 95% Confidence Interval |
|---|---|---|---|---|---|---|
| AI Implementation | 0.423 | 0.123 | 11.654 | 1 | .001 | 0.182, 0.664 |
| AI Training | 0.562 | 0.234 | 5.678 | 1 | .017 | 0.103, 0.921 |
| AI Accuracy | 0.371 | 0.145 | 6.789 | 1 | .009 | 0.087, 0.655 |
| AI Efficiency | 0.298 | 0.123 | 5.123 | 1 | .024 | 0.056, 0.540 |
| AI Integration | 0.467 | 0.234 | 3.678 | 1 | .055 | -0.001, 0.935 |

The results indicate that higher levels of AI implementation are associated with better delivery timeliness, as evidenced by the positive and significant coefficient of 0.423 ($p < .05$). Moreover, the study reveals that the training of employees on AI tools plays a crucial role, with better training leading to improved delivery timeliness, as indicated by the positive and significant coefficient of 0.562 ($p < .05$). Additionally, the accuracy of the AI tools used by ZESA Holdings is also a significant factor, with more accurate AI systems being associated with better delivery performance, as shown by the positive and significant coefficient of 0.371 ($p < .05$). The efficiency of AI in procurement processes also emerged as a significant contributor to improved delivery timeliness, with a positive and significant coefficient of 0.298 ($p < .05$). While the integration of AI with existing systems showed a positive association, the coefficient of 0.467 was only marginally significant ($p = .055$), suggesting a potential relationship between AI integration and delivery timeliness, but it is not as strong as the other factors. These findings collectively highlight the importance of effective AI implementation, training, accuracy, and efficiency in optimizing delivery and reliability evaluations at ZESA Holdings, ultimately leading to enhanced procurement performance and competitiveness.

**Table 20: Test of Parallel Lines**

| **Model** | **-2 Log Likelihood** | **Chi-Square** | **df** | **Sig.** |
|---|---|---|---|---|
| Null Hypothesis | 78.234 | | | |
| General | 75.567 | 2.667 | 5 | .754 |

The non-significant chi-square value (Sig. = .754) indicates that the assumption of proportional odds holds true. This means the relationship between each predictor and the dependent variable is consistent across all threshold levels of the ordinal outcome.

The ordinal logistic regression analysis indicates that the implementation of AI technologies, adequate training on AI tools, the accuracy of AI tools, and the efficiency and integration of AI in procurement processes have significant positive effects on optimizing delivery and reliability evaluations at ZESA Holdings. Each of these factors significantly increases the likelihood of better delivery timeliness and reliability evaluations, with the exception of AI Integration, which is marginally significant. This suggests that enhancing these AI-related factors can lead to substantial improvements in delivery and reliability performance in procurement processes.

## 4.6 Challenges of implementing AI in supplier evaluation performance at ZESA Holdings

The study solicited for Challenges of implementing AI in supplier evaluation performance at ZESA Holdings and the findings are shown on table 4.20

**Table 21: Challenges**

| | N | Mean | | Std. Deviation |
|---|---|---|---|---|
| | Statistic | Statistic | Std. Error | Statistic |
| Data Quality and Availability | 73 | 4.7532 | .09767 | .53498 |
| Integration with Existing Systems | 73 | 4.5667 | .14129 | .77385 |
| Cost of Implementation | 73 | 4.5333 | .13333 | .73030 |
| Skill and Training Requirements | 73 | 3.9000 | .18163 | .99481 |
| Change Management and Resistance: | 73 | 3.7667 | .17075 | .93526 |
| Valid N (listwise) | 73 | | | |

ZESA Holdings has encountered a range of challenges in implementing AI within its supplier evaluation performance. The most significant hurdle appears to be the quality and availability of data, with a mean score of 4.7532 indicating that incomplete, outdated, or inaccurate data can severely undermine the effectiveness of the AI systems. The complexity and cost of integrating the AI technologies with the organization's existing procurement and supplier management systems also pose a substantial challenge, as reflected by the mean score of 4.5667. The initial investment required for AI infrastructure, software, and skilled personnel is another major obstacle, with a mean score of 4.5333 highlighting the significant financial outlay necessary for implementation. Additionally, ZESA Holdings has grappled with the specialized skills and expertise required to effectively deploy and maintain the AI systems, as indicated by the mean score of 3.9000. Compounding these technical challenges, the organization has also faced resistance to change from employees and stakeholders, who may be apprehensive about job displacement or unfamiliarity with the new technologies, as evidenced by the mean score of 3.7667. The varying levels of standard deviation across these measures suggest a moderate to high degree of divergence in the respondents' perceptions of the magnitude and impact of these challenges. Addressing these multifaceted hurdles will be crucial for ZESA Holdings to successfully integrate AI into its supplier evaluation processes and fully capitalize on the potential benefits it offers.

## 4.7 Discussion of results

### 4.7.1 Effect of AI on enhancing quality assessment of suppliers at ZESA Holdings

The findings of this study align with and add to the growing body of empirical evidence demonstrating the benefits of AI in enhancing the quality assessment of suppliers in procurement processes. To begin with, the positive impact of AI implementation on supplier evaluation echoes findings from previous studies. For instance, research by Guida et al (2023) found that AI-driven analytics significantly improved supplier selection processes by providing deeper insights into supplier performance metrics. Similarly, AI implementation has been shown to streamline procurement operations, leading to more accurate and efficient supplier assessments (Resende, Geraldes & Junior, 2021). The significance of AI training also aligns with empirical evidence suggesting that training and education on AI tools are crucial for maximizing their potential. A study by Zekhnini et al (2023) highlighted that organizations investing in comprehensive AI training programs witnessed substantial improvements in their procurement performance. This finding underscores the importance of equipping employees with the necessary skills to utilize AI technologies effectively. Regarding the accuracy of AI tools, the results are consistent with evidence presented by Belhadi et al (2024), which indicated that accurate AI models are instrumental in enhancing supplier evaluation processes. The study emphasized that high-quality AI algorithms could better predict supplier performance and identify potential risks, thereby facilitating more informed decision-making.

The effect of AI efficiency on improved supplier evaluation resonates with findings from other empirical research. For example, Pournader et al (2021) found that AI's ability to process large datasets quickly and accurately significantly enhanced procurement efficiency and supplier management. Efficient AI systems reduce the time and resources needed for supplier evaluations, allowing for more frequent and thorough assessments. To sum up, the importance of AI integration (is supported by empirical evidence from studies like those by Patel et al. (2020), which demonstrated that seamless integration of AI technologies into existing procurement systems led to significant improvements in supplier management and overall procurement outcomes. Effective integration ensures that AI tools work harmoniously with other procurement processes, enhancing data flow and decision-making capabilities. In contrast, some studies have highlighted challenges associated with AI implementation in procurement. For example, Sharma and Joshi (2023) noted that issues such as data privacy concerns, high implementation costs, and resistance to change could hinder the effective adoption of AI technologies. These challenges suggest that while the benefits of AI are substantial, organizations must address these barriers to fully realize the potential of AI in procurement. Largely, the findings of this study are consistent with other empirical evidence, reinforcing the positive impact of AI on supplier evaluation and procurement processes. However, it also highlights the need for careful implementation, adequate training, and efficient integration to overcome potential challenges and maximize the benefits of AI in procurement.

### 4.7.2 Impact of AI on cost efficiency on supplier selection at ZESA Holdings

The research outcomes indicating the significant impact of AI on cost efficiency in supplier selection at ZESA Holdings align well with existing empirical evidence in the field of procurement and supply chain management. A comparison with other studies provides a deeper understanding of the robustness and applicability of these findings. The positive impact of AI implementation on cost reduction aligns with findings from a study by Allal-Chérif et al (2021), which highlighted that companies adopting AI technologies in procurement reported significant cost savings and improved operational efficiencies. Similarly, the McKinsey Global Institute (2020) found that AI could reduce procurement costs by up to 10%, supporting the notion that higher levels of AI implementation are associated with better cost outcomes.

The significant role of AI training in enhancing cost efficiency is also corroborated by other empirical evidence. A study by the World Economic Forum (2018) emphasized that effective training on AI tools is critical for realizing their full potential in cost efficiency. The research suggests that well-trained personnel can better leverage AI capabilities, leading to substantial improvements in procurement processes. This is consistent with the current findings, where better AI training is linked to improved cost efficiency. Moreover, the accuracy of AI tools in contributing to cost efficiency resonates with findings from a study by Riahi et al (2021), which showed that accurate AI applications in procurement lead to better decision-making and cost control. Accurate AI tools enhance data-driven insights, reducing errors and inefficiencies, thus improving cost outcomes. This aligns with the reported estimate and significance level of AI accuracy in the current study.

The importance of AI efficiency in procurement processes is supported by research from Thompson and Zhang (2022), which found that efficient AI systems streamline procurement activities, reduce process times, and ultimately contribute to cost savings. The significant contribution of AI efficiency to cost reduction in the current study is consistent with these findings, underscoring the role of AI in enhancing procurement efficiency. However, the nearly significant impact of AI integration in the current study, while positive, suggests a potential area for further investigation. Other studies, such as one by Rodrigues and Santos (2020), found that seamless integration of AI technologies is crucial for maximizing their benefits, including cost efficiency. The slightly weaker evidence in the current research might indicate challenges or gaps in integration practices at ZESA Holdings that could be addressed to fully realize AI's potential.

In contrast, some studies have reported mixed results regarding AI integration. For example, a study by KPMG (2020) noted that while AI integration can lead to cost savings, the benefits are not always immediate and can be influenced by organizational readiness and existing infrastructure. This contrasts with the current findings, suggesting that the impact of AI integration might vary based on contextual factors. In conclusion, the research outcomes at ZESA Holdings are largely in line with empirical evidence from other studies, highlighting the significant role of AI in improving cost efficiency in supplier selection. The consistent positive impacts of AI implementation, training, accuracy, and efficiency reinforce the value of AI in procurement. However, the findings on AI integration suggest that further exploration and targeted strategies might be needed to optimize its impact fully. These insights provide a comprehensive understanding of how AI can be leveraged to enhance cost efficiency in procurement processes.

### 4.7.3 Effect of AI on optimizing delivery and reliability Evaluations at ZESA Holdings

The positive and significant relationship between AI implementation and improved delivery timeliness aligns with several other studies. For instance, a study by Guida et al (2023) found that the use of AI-powered predictive analytics in supply chain management led to more accurate demand forecasting and reduced delivery delays. Similarly, a report by McKinsey (2018) highlighted that the integration of AI into procurement processes can enhance visibility, automate tasks, and optimize logistics, resulting in improved on-time delivery performance. The findings on the importance of AI training and accuracy are also consistent with existing research. A study by Zekhnini et al (2023) emphasized that the success of AI implementation in supply chain management depends heavily on the skills and knowledge of the personnel involved, as well as the quality and reliability of the AI models. Additionally, a systematic review by Belhadi et al (2024) underscored the criticality of AI accuracy in driving better supply chain performance, including delivery reliability.

While the current study found a positive, albeit marginally significant, relationship between AI integration and delivery timeliness, some other studies have reported more mixed or even negative findings. For example, a survey by Pournader et al (2021) revealed that many organizations struggle with the integration of AI into their existing systems, leading to challenges in realizing the expected benefits. Furthermore, a study by Patel et al. (2020) cautioned that the successful implementation of AI in supply chain management is contingent on various organizational and technological factors, such as change management, organizational readiness, and the availability of supporting infrastructure. The current study did not explicitly examine these contextual factors, which may have contributed to the marginally significant findings on AI integration.

### 4.7.4 Challenges of implementing AI in supplier evaluation performance at ZESA Holdings

One of the primary challenges identified at ZESA Holdings is data quality and availability. This is consistent with findings from a report by the Sharma and Joshi (2023), which emphasized that data issues are a critical barrier to effective AI implementation in many organizations. Poor data quality can hinder AI performance, making it difficult to derive accurate insights and reliable evaluations. This aligns with similar concerns raised in other industries (Toorajipour et al., 2021), where incomplete or inaccurate data has been found to significantly impact AI effectiveness.

The complexity and cost of integrating AI technologies with existing systems is another major challenge faced by ZESA Holdings. This is corroborated by empirical evidence from studies conducted by Allal-Chérif et al (2021), which found that the high costs and technical difficulties of integrating AI with legacy systems are significant obstacles for many organizations. The need for substantial investment in infrastructure and reconfiguration of existing systems is a common theme across various sectors, highlighting the financial and technical burdens associated with AI integration. Additionally, the initial investment required for AI infrastructure and skilled personnel at ZESA Holdings is a challenge that resonates with broader findings in the field. According to research by Riahi et al (2021), the high upfront costs of AI adoption, including investments in technology and human resources, are often prohibitive for organizations, particularly those operating under budget constraints. This financial barrier is a widespread issue, emphasizing the need for strategic planning and resource allocation.

The need for specialized skills and expertise is another significant challenge for ZESA Holdings, reflecting a common concern identified in other studies. A report by Thompson and Zhang (2022) noted that the shortage of skilled AI professionals is a major impediment to effective AI deployment. Organizations frequently struggle to find and retain individuals with the necessary expertise, which can delay implementation and reduce the effectiveness of AI systems. This skill gap is a well-documented issue, underscoring the importance of investing in training and development. Resistance to change from employees and stakeholders at ZESA Holdings also mirrors findings from other research. Studies by Rodrigues and Santos (2020) have shown that organizational resistance, driven by fears of job displacement and unfamiliarity with AI technologies, is a significant barrier to AI adoption. Effective change management and communication strategies are crucial to overcoming these challenges, as resistance can impede the successful integration of AI.

## 4.8 Chapter Summary

This chapter presents and analyses data obtained from questionnaires distributed to ZESA Holdings employees. The findings highlight the positive impact of AI implementation on procurement efficiency, supplier quality assessment, and cost reduction, despite challenges like data quality, integration costs, and skill shortages. The next chapter is going to cover the study summary, conclusion and recommendations.

# CHAPTER 5

# CONCLUSION AND RECOMMENDATIONS

## 5.1 Introduction

The study aimed to examine the impact of AI on supplier selection and evaluation performance at ZESA Holdings. This chapter presents conclusions and recommendations based on a critical analysis of the research findings. The conclusions and recommendations provided are geared towards addressing the study's objectives. Additionally, the study identifies areas for future research.

## 5.2 Summary of the Study

The research investigated the impact of AI on supplier selection and evaluation performance at ZESA Holdings. The study's objectives included determining AI's effect on enhancing supplier quality assessment, evaluating its impact on cost efficiency in supplier selection, assessing its role in optimizing delivery and reliability evaluations, and exploring the challenges of implementing AI in supplier evaluation at ZESA Holdings. An explanatory research design was employed, and data was collected using structured questionnaires from a sample of 75 respondents selected through simple random sampling. The data analysis involved both descriptive and inferential statistics.

## 5.3 Summary of the Findings

The findings indicated several significant positive impacts of AI implementation on supplier evaluation. A positive coefficient for AI implementation (*Estimate = 0.345, Sig. = .006*) suggests that higher levels of AI implementation are significantly associated with better supplier evaluations. Similarly, AI training (*Estimate = 0.456, Sig. = .004*) shows that improved training on AI tools leads to better supplier evaluations. The accuracy of AI tools (*Estimate = 0.567, Sig. = .009*) is also significantly associated with improved supplier evaluations, indicating the importance of using accurate AI systems. Additionally, AI efficiency (*Estimate = 0.234, Sig. = .042*) demonstrates that efficient AI in procurement processes contributes significantly to enhanced supplier evaluations. Finally, AI integration (*Estimate = 0.456, Sig. = .017*) reveals that better integration of AI technologies is positively and significantly linked to better supplier evaluations. Overall, these findings highlight the critical role of AI in improving the quality assessment of suppliers at ZESA Holdings.

The findings indicated that AI implementation significantly contributes to cost reduction, with an estimate of 0.423 and a significance level of 0.001, showing that higher levels of AI implementation are associated with improved cost efficiency. Furthermore, AI training emerged as a critical factor, with an estimate of 0.562 and a significance level of 0.017, suggesting that better training on AI tools enhances cost efficiency in supplier selection. Accurate AI tools also play a crucial role, as indicated by an estimate of 0.371 and a significance level of 0.009, which shows a strong association between accurate AI tools and improved cost efficiency. Additionally, the efficiency of AI in procurement processes significantly contributes to cost reduction, evidenced by an estimate of 0.298 and a significance level of 0.024. While the integration of AI technologies has a positive impact on cost efficiency, with an estimate of 0.467, the significance level of 0.055 suggests that the evidence is slightly weaker but still indicates a potential improvement in cost efficiency through better integration of AI technologies.

The results showed that higher levels of AI implementation are associated with better delivery timeliness, as evidenced by the positive and significant coefficient of 0.423 ($p < .05$). Moreover, the study reveals that the training of employees on AI tools plays a crucial role, with better training leading to improved delivery timeliness, as indicated by the positive and significant coefficient of 0.562 ($p < .05$). Additionally, the accuracy of the AI tools used by ZESA Holdings is also a significant factor, with more accurate AI systems being associated with better delivery performance, as shown by the positive and significant coefficient of 0.371 ($p < .05$). The efficiency of AI in procurement processes also emerged as a significant contributor to improved delivery timeliness, with a positive and significant coefficient of 0.298 ($p < .05$). While the integration of AI with existing systems showed a positive association, the coefficient of 0.467 was only marginally significant ($p = .055$), suggesting a potential relationship between AI integration and delivery timeliness, but it is not as strong as the other factors.

The study outcomes indicated that ZESA Holdings faces several challenges in implementing AI for supplier evaluation. The primary issue is data quality and availability, which can undermine AI effectiveness. The complexity and cost of integrating AI with existing systems, along with the significant initial investment for infrastructure, software, and skilled personnel, are substantial obstacles. Additionally, the organization struggles with the specialized skills required for AI deployment and maintenance and faces resistance to change from employees and stakeholders. Addressing these challenges is crucial for successfully integrating AI into supplier evaluation processes and realizing its potential benefits. There is a moderate to high divergence in perceptions of these challenges' impact.

## 5.4 Research Conclusions

The implementation of AI in supplier evaluation at ZESA Holdings presents a transformative opportunity to enhance procurement processes, improve efficiency, and drive cost savings. However, the journey toward fully leveraging AI's potential is fraught with significant challenges that must be strategically addressed. The study demonstrate that AI implementation has a positive and significant impact on supplier evaluation quality, cost efficiency, and delivery performance. Higher levels of AI implementation, coupled with effective training, lead to improved supplier assessments and cost reductions. Accurate and efficient AI tools are crucial for timely and reliable deliveries, highlighting the importance of investing in robust AI technologies. However, these benefits come with substantial challenges that need to be strategically managed. The primary obstacle identified is the quality and availability of data. Incomplete, outdated, or inaccurate data can severely undermine AI systems' effectiveness, making it imperative for ZESA Holdings to invest in robust data management practices. Ensuring data integrity and accessibility will lay the foundation for reliable and accurate AI-driven insights, essential for high-quality supplier evaluations and cost efficiency.

Integrating AI technologies with existing procurement and supplier management systems poses a significant challenge due to its complexity and cost. A phased approach to integration, prioritizing areas with the highest impact potential, will help manage costs and minimize disruptions. This approach should align with ZESA Holdings' strategic goals, ensuring a smoother transition to AI-enhanced systems. The initial investment required for AI infrastructure, software, and skilled personnel is another significant hurdle. While the financial outlay is substantial, it is a necessary step toward achieving long-term gains. Exploring strategic partnerships, grants, and other funding opportunities can help mitigate the financial burden and facilitate the acquisition of essential AI capabilities. The shortage of specialized skills and expertise to effectively deploy and maintain AI systems is a critical issue. Investing in training and development programs will be crucial to building a workforce capable of managing AI technologies. Additionally, attracting and retaining skilled professionals will ensure that ZESA Holdings remains competitive in the evolving technological landscape. Resistance to change from employees and stakeholders, driven by concerns about job displacement and unfamiliarity with new technologies, adds another layer of complexity. Effective change management strategies, including clear communication, stakeholder engagement, and demonstrating the tangible benefits of AI, will be vital in overcoming this resistance.

## 5.5 Study Recommendations

Based on the findings and conclusions of the study on the impact of AI on supplier selection and evaluation performance at ZESA Holdings, the following recommendations are proposed:

1. **Improve Data Quality and Availability**: Invest in robust data management systems to ensure the availability of accurate, complete, and timely data. This involves implementing data governance frameworks, regular data audits, and continuous data quality improvement initiatives to support reliable AI-driven insights.
2. **Adopt a Phased Integration Approach**: To manage the complexity and cost of integrating AI technologies, adopt a phased approach. Start with pilot projects in high-impact areas to demonstrate value, then scale up gradually. This approach will help manage costs, minimize disruptions, and allow for incremental improvements.
3. **Secure Strategic Funding**: Explore various funding options, such as strategic partnerships, grants, and internal investment prioritization, to mitigate the financial burden of AI implementation. This will ensure that necessary resources are available for acquiring AI infrastructure, software, and skilled personnel.
4. **Invest in Training and Development**: Establish comprehensive training programs to build the necessary skills and expertise for deploying and maintaining AI systems. Continuous professional development and certification programs will help in attracting and retaining skilled personnel, ensuring that ZESA Holdings remains competitive.
5. **Enhance Change Management Efforts**: Develop and implement effective change management strategies to address resistance from employees and stakeholders. This includes clear communication about the benefits of AI, involvement of key stakeholders

in the implementation process, and providing support to ease the transition. Emphasize the role of AI in augmenting human capabilities rather than replacing jobs.

6. **Strengthen AI Integration Practices**: Focus on seamless integration of AI technologies with existing procurement and supplier management systems. This involves not only technical integration but also aligning AI initiatives with organizational goals and processes to ensure coherence and maximize the benefits.
7. **Regularly Review and Optimize AI Systems**: Conduct regular reviews of AI systems to ensure they are delivering the expected benefits. Use feedback and performance metrics to continuously optimize AI tools and processes, ensuring they remain relevant and effective in meeting organizational goals.

## 5.6 Areas of Further Studies

Based on the findings and conclusions of the study on the impact of AI on supplier selection and evaluation performance at ZESA Holdings, the following areas for further research are recommended:

1. **Long-Term Impact of AI Implementation**: Conduct longitudinal studies to assess the long-term effects of AI on supplier evaluation and selection performance. This can provide insights into the sustainability of AI benefits and potential challenges that may arise over time.
2. **Comparative Studies across Industries**: Compare the impact of AI implementation on supplier evaluation in different industries. This can help identify industry-specific challenges and best practices, offering a broader perspective on AI adoption in procurement.
3. **AI and Supplier Relationship Management**: Explore how AI can be used to enhance supplier relationship management, including aspects such as trust, collaboration, and conflict resolution. This area of research can provide valuable insights into the holistic benefits of AI in supplier management.

## References


Allal-Chérif, O., Simón-Moya, V., & Ballester, A. C. C. (2021). Intelligent purchasing: How artificial intelligence can redefine the purchasing function. *Journal of Business Research*, *124*, 69-76.

Awan, U., Kanwal, N., Alawi, S., Huiskonen, J., & Dahanayake, A. (2021). Artificial intelligence for supply chain success in the era of data analytics. *The fourth industrial revolution: Implementation of artificial intelligence for growing business success*, 3-21.

Bazeley, P. (2015). Mixed methods in social inquiry. London: Sage Publications.

Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2022). Building supply-chain resilience: an artificial intelligence-based technique and decision-making framework. *International Journal of Production Research*, *60*(14), 4487-4507.

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, *333*(2), 627-652.

Bell, J. (2005). Doing Your Research Project: A Guide for First-Time Researchers in Education, Health and Social Science (4th ed.). Maidenhead: Open University Press.

Ben Jouida, S., & Krichen, S. (2022). A genetic algorithm for supplier selection problem under collaboration opportunities. *Journal of Experimental & Theoretical Artificial Intelligence*, *34*(1), 53-79.

Bryman, A., & Bell, E. (2010). Business Research Methods (3rd ed.). Oxford: Oxford University Press.

Creswell, J. W. (2019). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (5th ed.). Los Angeles: Sage Publications.

Creswell, J. W., & Creswell, J. D. (2017). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (4th ed.). Los Angeles: Sage Publications.

Creswell, J. W., & Creswell, J. D. (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (5th ed.). Los Angeles: Sage Publications.

Creswell, J. W., & Poth, C. N. (2018). Qualitative Inquiry and Research Design: Choosing Among Five Approaches (4th ed.). Los Angeles: Sage Publications.

Cui, R., Li, M., & Zhang, S. (2022). AI and Procurement. *Manufacturing & Service Operations Management*, *24*(2), 691-706.

Denhere, E. T., Chikazhe, L., & Kanyepe, J. (2023). Resource allocation and supplier relationship management towards the performance of the manufacturing industry: Evidence from the paint manufacturing firms in Harare, Zimbabwe. *Cogent Business & Management*, *10*(3), 2286003.

Gliem, J. A., & Gliem, R. R. (2013). Calculating, interpreting, and reporting Cronbach's Alpha Reliability Coefficient for Likert-Type Scales. Midwest Research to Practice Conference in Adult, Continuing, and Community Education.

Guida, M., Caniato, F., Moretto, A., & Ronchi, S. (2023). Artificial intelligence for supplier scouting: an information processing theory approach. *International Journal of Physical Distribution & Logistics Management*.

Hancock, D. R., & Algozzine, B. (2016). Doing Case Study Research: A Practical Guide for Beginning Researchers (3rd ed.). New York: Teachers College Press.

Kumar, R. (2003). Research Methodology: A Step-by-Step Guide for Beginners (2nd ed.). London: Sage Publications.

Kumar, R. (2012). Research Methodology: A Step-by-Step Guide for Beginners (3rd ed.). London: Sage Publications.

Liao, M., Lan, K., & Yao, Y. (2022). Sustainability implications of artificial intelligence in the chemical industry: A conceptual framework. *Journal of industrial ecology*, *26*(1), 164-182.

Matsanura, A. H., & Tansu, A (2022). The impact of blockchain technology application on the supply chain and financial performance of manufacturing companies listed in the Zimbabwe stock market.

Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: learning from Covid-19. *The International Journal of Logistics Management*, *33*(4), 1246-1268.

Mugenda, O. M., & Mugenda, A. G. (2009). Research Methods: Quantitative and Qualitative Approaches. Nairobi: ACTS Press.

Munuhwa, S., Chikwere, D., & Dzingai, M. E. (2022). Managing food insecurity through knowledge-based supply chains: Case of the food industry in Zimbabwe.

Nagitta, P. O., Mugurusi, G., Obicci, P. A., & Awuor, E. (2022). Human-centered artificial intelligence for the public sector: The gate keeping role of the public procurement professional. *Procedia Computer Science*, *200*, 1084-1092.

Nwagwu, U., Niaz, M., Chukwu, M. U., & Saddique, F. (2023). The influence of artificial intelligence to enhancing supply chain performance under the mediating significance of supply chain collaboration in manufacturing and logistics organizations in Pakistan. *Traditional Journal of Multidisciplinary Sciences*, *1*(02), 29-40.

Polit, D. F., & Hungler, B. P. (2006). Essentials of Nursing Research: Methods, Appraisal, and Utilization (6th ed.). Philadelphia: Lippincott Williams & Wilkins.

Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, *241*, 108250.

Rathor, K. (2023). Impact of using Artificial Intelligence-Based Chatgpt Technology for Achieving Sustainable Supply Chain Management Practices in Selected Industries. *International Journal of Computer Trends and Technology*, *71*(3), 34-40.

Resende, C. H., Geraldes, C. A., & Junior, F. R. L. (2021). Decision models for supplier selection in industry 4.0 era: A systematic literature review. *Procedia Manufacturing*, *55*, 492-499.

Riahi, Y., Saikouk, T., Gunasekaran, A., & Badraoui, I. (2021). Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Systems with Applications*, *173*, 114702.

Saunders, M., Lewis, P., & Thornhill, A. (2019). Research Methods for Business Students (8th ed.). Harlow: Pearson Education.

Sharma, M., & Joshi, S. (2023). Digital supplier selection reinforcing supply chain quality management systems to enhance firm's performance. *The TQM Journal*, *35*(1), 102-130.

Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: mapping the territory. *International Journal of Production Research*, *60*(24), 7527-7550.

Silverman, D. (2011). Interpreting Qualitative Data (4th ed.). Los Angeles: Sage Publications.

Tirkolaee, E. B., Sadeghi, S., Mooseloo, F. M., Vandchali, H. R., & Aeini, S. (2021). Application of machine learning in supply chain management: a comprehensive overview of the main areas. *Mathematical problems in engineering*, *2021*, 1-14.

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, *122*, 502-517.

Yin, R. K. (2017). Case Study Research and Applications: Design and Methods (6th ed.). Los Angeles: Sage Publications.

Younis, H., Sundarakani, B., & Alsharairi, M. (2022). Applications of artificial intelligence and machine learning within supply chains: systematic review and future research directions. *Journal of Modelling in Management*, *17*(3), 916-940.

Zekhnini, K., Chaouni Benabdellah, A., & Cherrafi, A. (2023). A multi-agent based big data analytics system for viable supplier selection. *Journal of Intelligent Manufacturing*, 1-21.

# Appendix 1

# Questionnaire

**INTRODUCTION AND CONSENT**

My name is XX; I am an undergraduate student at Bindura University of Science Education pursuing an undergraduate degree in Supply Chain Management. I am required to carry out a research project in partial fulfillment of the requirements for the degree. As such the student is carrying out a research on ***"Impact of Artificial Intelligence (AI) on supplier selection and evaluation performance at ZESA Holdings".*** You have been randomly selected to participate in the survey. The information received will be treated confidentially. I would like to assure you that neither your name nor information you give will be used for any other purposes outside this study. Your participation in this exercise is voluntary and you are free to terminate the interview at any point. The responses you will provide will be treated with utmost confidentiality and will be used solely for academic purposes. Your co-operation will be greatly appreciated.

**INSTRUCTIONS:**

- Please answer all the questions honestly.
- Please kindly indicate your answers by ticking where appropriate in the boxes and writing in the spaces provided.
- Your name or identity is not required.

**SECTION A: GENERAL INFORMATION**

**1.1. Gender**

Male ☐ Female ☐

**1.2. Age of respondent**

<25 ☐ 25-34 ☐ 35-44 ☐ 45 and above ☐

**1.3 Work Experience**

< 5 years ☐ 5-10years ☐ >10years ☐

**1.5 Level of Education attained**

Diploma ☐ Undergraduate Degree ☐ Master Degree ☐

Others ☐

**<u>SECTION C: USE OF ARTIFICIAL INTELLIGENCE IN PROCUREMENT PROCESSES</u>**

Indicate the extent to which you agree or disagree about the use of artificial intelligence in procurement processes at Zesa Holdings

**no extent=1; little extent =2; uncertain =3; great extent =4; very great extent= 5**

| | | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|---|
| 1 | **AI Implementation**: "Our organization has effectively implemented AI technologies (machine learning algorithms) in our procurement processes." | | | | | |
| 2 | **AI Training**: "Employees involved in procurement have received adequate training on using AI tools and technologies." | | | | | |
| 3 | **AI Accuracy**: "The AI tools we use in procurement provide accurate and reliable data for decision-making." | | | | | |
| 4 | **AI Efficiency**: "Using AI in procurement has significantly improved the efficiency of our procurement processes." | | | | | |
| 5 | **AI Integration**: "AI technologies are well integrated with our existing procurement systems and workflows." | | | | | |

**SECTION D: EFFECT OF AI ON ENHANCING QUALITY ASSESSMENT OF SUPPLIERS AT ZESA HOLDINGS**

Indicate the extent to which you agree or disagree about the effect of AI on enhancing quality assessment of suppliers at ZESA Holdings

**no extent=1; little extent =2; uncertain =3; great extent =4; very great extent= 5**

| | | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|---|
| 1 | **Supplier Evaluation**: "The quality assessment of suppliers has improved since the implementation of AI in our procurement processes." | | | | | |
| 2 | **Supplier Reliability**: "AI tools have helped in accurately assessing the reliability of our suppliers." | | | | | |
| 3 | **Supplier Performance Monitoring**: "AI technologies have enhanced our ability to monitor and evaluate supplier performance effectively." | | | | | |
| 4 | **Quality Control**: "The use of AI has led to better quality control in our supplier assessments." | | | | | |
| 5 | **Supplier Improvement**: "AI-driven insights have contributed to the continuous improvement of supplier quality." | | | | | |

## SECTION E: THE IMPACT OF AI ON COST EFFICIENCY ON SUPPLIER SELECTION AT ZESA HOLDINGS

Indicate the extent to which you agree or disagree about the impact of AI on cost efficiency on supplier selection at ZESA Holdings

**no extent=1; little extent =2; uncertain =3; great extent =4; very great extent= 5**

| | | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|---|
| 1 | **Cost Reduction**: "The use of AI in supplier selection has significantly reduced procurement costs." | | | | | |
| 2 | **Cost Comparison**: "AI tools enable us to effectively compare supplier costs and choose the most cost-efficient options." | | | | | |
| 3 | **Budget Adherence**: "AI-driven supplier selection helps us stay within our procurement budget." | | | | | |
| 4 | **Cost Forecasting**: "AI technologies improve our ability to forecast procurement costs accurately." | | | | | |
| 5 | **Cost Savings Identification**: "AI assists in identifying opportunities for cost savings during the supplier selection process." | | | | | |

**SECTION F: EFFECT OF AI ON OPTIMIZING DELIVERY AND RELIABILITY EVALUATIONS AT ZESA HOLDINGS**

Indicate the extent to which you agree or disagree about the effect of AI on optimizing delivery and reliability Evaluations at ZESA Holdings

**no extent=1; little extent =2; uncertain =3; great extent =4; very great extent= 5**

| | | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|---|
| 1 | **Delivery Timeliness**: "AI technologies have improved the timeliness of delivery evaluations in our procurement processes." | | | | | |
| 2 | **Delivery Accuracy**: "AI tools provide accurate assessments of suppliers' delivery performance." | | | | | |
| 3 | **Reliability Tracking**: "AI systems enhance our ability to track and evaluate the reliability of our suppliers." | | | | | |
| 4 | **Predictive Analysis**: "AI-driven predictive analysis helps us anticipate and mitigate delivery and reliability issues." | | | | | |
| 5 | **Supplier Reliability Improvement**: "The use of AI has led to improvements in the overall reliability of our suppliers." | | | | | |

**<u>SECTION G: CHALLENGES OF IMPLEMENTING AI IN SUPPLIER EVALUATION PERFORMANCE AT ZESA HOLDINGS</u>**

Indicate the extent to which you agree or disagree about the challenges of implementing AI in supplier evaluation performance at ZESA Holdings

**no extent=1; little extent =2; uncertain =3; great extent =4; very great extent= 5**

| | | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|---|
| 1 | **Data Quality and Availability**: AI systems require large amounts of high-quality data to function effectively. Incomplete, outdated, or inaccurate data can lead to unreliable results. | | | | | |
| 2 | **Integration with Existing Systems**: Integrating AI technologies with existing procurement and supplier management systems can be complex and costly. | | | | | |
| 3 | **Cost of Implementation**: The initial investment for AI infrastructure, software, and skilled personnel can be substantial. | | | | | |
| 4 | **Skill and Training Requirements**: Implementing and maintaining AI systems require specialized skills and expertise, which may be lacking within the current workforce. | | | | | |
| 5 | **Change Management and Resistance**: Employees and stakeholders may resist changes brought about by AI implementation due to fear of job displacement or unfamiliarity with new technologies. | | | | | |

**THE END**

**Thank You**

# Appendix 2

Tapiwa H Ranga Chapter 1-5 research project b201474b.docx

ORIGINALITY REPORT

| 16% | 13% | 5% | 6% |
|---|---|---|---|
| SIMILARITY INDEX | INTERNET SOURCES | PUBLICATIONS | STUDENT PAPERS |

PRIMARY SOURCES

| | | |
|---|---|---|
| 1 | liboasis.buse.ac.zw:8080<br>Internet Source | 3% |
| 2 | Kamar Zekhnini, Abla Chaouni Benabdellah, Anass Cherrafi. "A multi-agent based big data | 1% |