THE IMPACT OF AI-ENABLED GRAIN STORAGE ON AGRICULTURAL DEVELOPMENT PROGRAMMES: A CASE OF GMB KWEKWE DEPOT, ZIMBABWE

A dissertation submitted in partial fulfilment of the requirements for the Master of Science Degree in Food Security and Sustainable Agricultural Policy

Bindura University of Science Education

Faculty of Agriculture and Environmental Science

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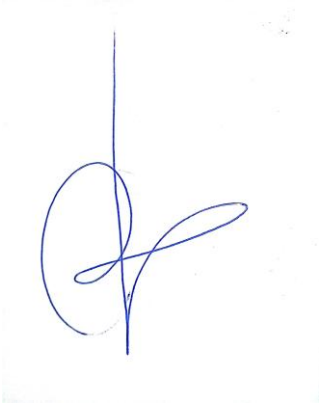
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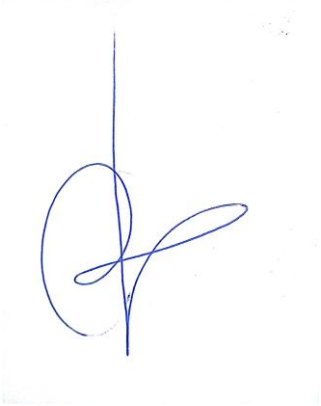
DECLARATION

I hereby declare that the research project entitled **THE IMPACT OF AI-ENABLED GRAIN STORAGE ON AGRICULTURAL DEVELOPMENT PROGRAMMES: A CASE OF GMB KWEKWE DEPOT, ZIMBABWE** submitted to Bindura University of Science Education, Department of Agricultural Economics, Education and Extension is a record of an original work done by me under the guidance and supervision of **DR N MAFUSE** and this work is submitted in partial fulfilment of the requirements for the award of a Master of Science Degree in Food Security and Sustainable Agriculture. The results embodied in this thesis have not been submitted to any University or Institute for the award of any degree of diploma.

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ABSTRACT

The study investigated the effects of AI-based grain storage on the success of agricultural development programs in Grain Marketing Board (GMB) Kwekwe depot, Zimbabwe. The motivation for the study was due to the continued problems with post-harvest losses, low efficiency in the operation of grain storage facilities and the increasing need for new technology that would improve agricultural production. In this context, the research sought to investigate the effect of AI-based grain storage on the reduction of post-harvest losses, increased efficiency, agricultural development, and issues associated with adopting new technologies in grain storage. This research adopted the positivist approach to research while using a quantitative research methodology. The data collection tool employed in this research included a structured questionnaire which targeted thirty respondents consisting of employees, farmers and management of GMB. A total of 30 questionnaires were sent out, but 27 were completed and received, indicating a response rate of 90%. Data analysis involved the use of descriptive statistics such as frequencies, percentages, and central tendency measures for quantitative data, and thematic analysis for qualitative data.

From the results, it was evident that the respondents considered post-harvest losses a problem within grain storage. It was clear from the research that artificial intelligence grain storage has an impact on reducing the losses caused by grain spoilage through enhanced monitoring, moisture control, pest management, and good storage procedures. Additionally, respondents agreed that artificial intelligence helps in improving efficiency through monitoring, labour savings, efficient inventory management, and better decision making. Finally, respondents indicated that AI systems help in contributing to food security, grain management, and agriculture development through reduced losses. However, limitations in adoption include lack

of knowledge, high cost, poor infrastructure, and reluctance to adapt. There exist several opportunities, such as better monitoring, efficiency improvement, loss reduction, and profitability improvement. The research found out that the use of AI technology in grain storage is having a considerable positive effect on the agricultural development projects due to its role in minimizing losses, enhancing efficiency, and ensuring food security.

Keywords: Artificial Intelligence, Grain Storage, Post-Harvest Losses, Food Security, Agricultural Development, Operational Efficiency, Zimbabwe.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
AI	Artificial Intelligence
DOI	Diffusion of Innovation
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
GMB	Grain Marketing Board
ICT	Information and Communication Technology
IoT	Internet of Things
SDGs	Sustainable Development Goals
TAM	Technology Acceptance Model
UN	United Nations
WB	World Bank

Abbreviation Meaning

ZIMSTAT Zimbabwe National Statistics Agency

Chapter one

Introduction

1.0 Introduction

This chapter introduces the study by giving the global and national context of food insecurity and post-harvest losses, showing how they impact agricultural productivity. It outlines the relevance of AI in making grain storage efficient and situates the problem within Zimbabwe's agricultural sector, particularly at the Kwekwe GMB. The introduction provides a background on how AI-enabled grain storage can contribute toward attainment of food security and agricultural development programs in line with national modernization goals.

1.1 Background of the study

Food insecurity is a significant global challenge, added to by climate shocks, pandemics, and supply chain disruptions. It is approximated by the Food and Agriculture Organization (FAO, 2021) that approximately 828 million people experienced undernourishment in 2020, increasing from previous years. Among the key reasons for this phenomenon is post-harvest loss, which

FAO (2019) approximates to account for 14% of food production losses worldwide before goods reach retail markets. Grains, legumes, and cereals billion's staples are particularly prone to deterioration by improper handling, insects, and inadequate storage (Parfitt et al., 2019; Hodges et al., 2014). Economically, these losses amount to billions of dollars annually and compound world malnutrition.

Food insecurity is a crucial global concern, affecting millions of people worldwide. According to the Food and Agriculture Organization (FAO, 2021), almost 828 million people were undernourished in 2020, an increase from over 46 million since 2019. The surge was led by a set of climate shocks, conflict, economic instability, and supply chain disruptions in global food systems initiated by pandemics such as COVID-19. The least covered but most significant source of food insecurity is post-harvest loss, which the FAO (2019) estimates causes 14% of food losses worldwide prior to fruits and vegetables being ready for retail markets. Grains and cereals are disproportionately affected by post-harvest loss, and these are the staple diet for millions of people worldwide (Hodges et al., 2014; Parfitt et al., 2019). These losses not only decrease food quantities but also entail very high economic losses, estimated at USD 400 billion annually, apart from exacerbating malnutrition in vulnerable populations (Gustavsson et al., 2011).

Post-harvest losses (PHL) are a global issue, particularly in developing nations where agricultural infrastructure is often not available. The Food and Agriculture Organization (FAO) states that almost 13.2% of the food produced globally is lost after harvest, such as during on-farm handling, processing, and storage (FAO, 2021). Loss is greater in Sub-Saharan Africa, where as much as 30% to 50% of every year's production is lost, with an estimated value of approximately 1.3 billion metric tons (APHLIS, 2020). These are due to conditions such as inadequate storage facilities, inadequate transportation, and lack of access to new preservation technologies.

In the case of Africa, post-harvest losses are even higher given that there is inadequate infrastructure, inadequate access to modern storage technology, and climatic exposure. It is estimated that sub-Saharan Africa loses 37% of the food it produces each year, with cereals such as maize and sorghum losing between 15% and 25% when it is stored using pests, mold, and inadequate drying methods (Affognon et al., 2015; World Bank, 2018). The African Postharvest Losses Information System (APHLIS, 2020) estimates that farmers in East and Southern Africa

collectively lose over USD 4 billion annually, an enormous loss in household incomes and food availability. The Kitinoja and Kader (2015) research emphasizes that minimizing post-harvest losses in cereals contributes to increasing economic benefits to farmers as well as food security in the region. With the lack of adequate storage, surplus harvests are wasted, markets become unstable, and the incentive for farm production becomes lower, offering a destructive cycle to food sustainability.

In Africa, post-harvest losses are far too high due to infrastructural limitations and climatic exposures. Sub-Saharan Africa is reported to lose 37% of all food harvested each year, while staple cereals such as maize, sorghum, and millet lose 15–25% during storage (Affognon et al., 2015; World Bank, 2018). Estimates from the African Postharvest Losses Information System (APHLIS, 2020) suggest that individual smallholder farmers in East and Southern Africa lose food worth over USD 4 billion each year due to poor storage and pest infestation. Not only do the losses impact household nutrition, but they also discourage investment in agriculture and reduce the ability of farmers to absorb market and climatic shocks.

Maize is the leading crop in both production and consumption in Zimbabwe, being the food staple for more than 70% of the population (FAO, 2021). Post-harvest loss is estimated at 15–20% of the total maize production each year, mainly caused by poor drying, poor storage facilities, and pest damage (Mhlanga, 2014; FAO, 2021). The Grain Marketing Board, created in 1931 to oversee strategic grain storage, is challenged by old silos, inadequate modernization, and non-uniform operating procedures (Mudzonga, 2011). Climate variability characterized by unpredictable rainfall and extended dry seasons further complicates the consistency of the harvest, necessitating effective storage to avoid food shortages. Historical patterns show that Zimbabwe has, in some years, been exporting maize amidst surplus production, clearly a sign of the urgent need for modern storage facilities (Nhamo, 2019).

This is most urgent in Midlands Province, whose central grain depot is Kwekwe. Being situated at the hub of large road and rail networks, Kwekwe has an easy time harvesting grains from surrounding areas of agriculture and shipping them nationwide. The Midlands region contributes to a high percentage of national maize production, yet the majority of smallholder farmers lack access to improved storage facilities, and therefore they risk high post-harvest losses. The evidence indicates that post-harvest handling interventions like utilization of new silo technology

can reduce losses by 30–50%, enhance farmer incomes, as well as regional and national food security levels (World Bank, 2018; Kitinoja & Kader, 2015). Having a new Artificial Insemination (AI) silo facility in Kwekwe would therefore actually reinforce GMB's operating effectiveness directly, stabilise supply in the market, benefit local farmers, and fulfill national goals such as Zimbabwe Vision 2030, which is centred on agricultural modernisation, food self-sufficiency, and poverty reduction (Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2021).

Kwekwe, located in the Midlands Province, presents a strategic site for addressing Zimbabwe's post-harvest challenges. It lies at a major transport nexus, linking road and rail networks that facilitate grain collection from surrounding farming districts and distribution nationwide. The Midlands region is a key maize-producing area, yet smallholder farmers frequently lack access to modern storage facilities. Its investment in a modern AI silo plant in Kwekwe would solidify GMB's capacity to store and off-load grain efficiently, reduce losses, stabilize market inventory, and enhance food security. The initiative aligns with Zimbabwe's Vision 2030, which emphasizes agricultural modernization and food self-sufficiency as pillars for achieving upper-middle-income status, while simultaneously supporting the global Sustainable Development Goal 2 of ending hunger and promoting sustainable agriculture (Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2021).

1.2 Statement of the Problem

Agriculture is still the mainstay of the Zimbabwean economy and a pillar of national food security, but the sector is stricken with endemic difficulties associated with post-harvest losses, storage facilities, and antiquated management practices. The Grain Marketing Board (GMB) responsible for the nation's strategic grain reserves is still relying on manual monitoring systems, poor ventilation, and aging silos that undermine both grain quality and operational performance. At retail outlets such as the Kwekwe depot in Midlands Province, the absence of sophisticated environmental controls allows excessive moisture, temperature fluctuation, and pest infestation to deteriorate stored grain, particularly at harvest time during the rainy season. As a result, Zimbabwe loses as much as 30% of its yearly cereal production (Bongi & Chikozho, 2020), thereby reducing farmers' incomes and reducing national grain stocks. These inefficiencies

chronically undermine the effectiveness of food security policy and degrade the sustainability of agricultural development programs.

Lack of Artificial Intelligence (AI) integration in GMB operations leaves wide technology and strategy gaps. Sluggish, reactive manual processes cannot anticipate or prevent spoilage in real-time. In contrast, AI-enabled systems incorporating smart sensors, predictive analytics, and automated environmental controls—could transform storage management by enabling early detection of spoilage risks, optimizing resource use, and improving accountability. Without such innovation, post-harvest losses will continue to strain Zimbabwe's food systems and economic stability. This research therefore seeks to analyze the feasibility of Artificial Intelligence-based grain stores in improving efficiency of operations, reducing post-harvest losses, and improving national food security at the Kwekwe GMB depot.

1.3 Study Objectives

1.3.1 Main Objective

To investigate the role of Artificial Intelligence (AI)-enabled grain storage facilities in enhancing agricultural development programs in Zimbabwe, based on a case study of the Kwekwe GMB warehouse.

1.3.2 Specific Objectives

- To analyze the impact of AI-enabled grain storage on reducing post-harvest losses at Kwekwe GMB.
- To investigate how AI-enabled storage facilities improve operational efficiency and grain quality management.
- To examine the contribution of AI-based storage to agricultural development programs, particularly to smallholder farmers.
- To identify challenges and opportunities in application and utilization of AI technologies by grain storage facilities in Zimbabwe.

1.4 Research Questions

1. How can AI-based grain storage reduce post-harvest losses for Kwekwe GMB?
2. How does AI technology increase operational efficiency and quality management of grains in storage facilities?
3. How does the use of AI-based storage help drive agricultural development projects in Zimbabwe?
4. What are the facilitators and inhibitors for the use of AI-based grain storage in Zimbabwe?

1.5 Hypotheses

Hypothesis 1 (H1): AI-based grain storage has a significant impact on post-harvest losses at Kwekwe GMB.

Hypothesis 2 (H2): AI-based grain storage has a significant impact on operational efficiency and grain quality management.

Hypothesis 3 (H3): Grain storage augmented by AI contributes to the effectiveness of agricultural development programs positively

1.6 Significance of the Study

The significance of a study refers to its importance and the contribution it makes to existing knowledge, practice, or policy. In this study, the focus is on understanding how Artificial Intelligence (AI)-enabled grain storage systems can address persistent challenges in Zimbabwe's agricultural sector, such as post-harvest losses, inefficient storage practices, and limited technology adoption. Through the examination of Kwekwe Grain Marketing Board (GMB) warehouse, the research is intended to provide evidence on how AI technologies can improve storage operations, food safety, and agricultural development schemes. AI-enabled grain storage systems are capable of reducing losses by regulating the storage environment and enabling predictive monitoring, thus improving operational effectiveness and grain quality control (Anukiruthika & Jayas, 2025). This study is hence justified because it contributes towards

achieving the future potential of AI to influence post-harvest management, improve farmer livelihoods, and promote sustainable agricultural development in Zimbabwe (Hove, Ngwenya, & Madhazi, 2024).

1.7 Study Scope and Delimitations

The scope of a study defines the extent and focus of the research. This research is limited to the examination of AI-based grain storage systems within the Kwekwe GMB Zimbabwe facility, focusing on their role in post-harvest loss reduction, operational effectiveness, and contribution to agricultural development programs. Delimitations refer to the intentional limits established by the researcher to keep the focus. Here, the research omits other facilities of the GMB in Zimbabwe and does not encompass non-AI-based post-harvest interventions or general agriculture technologies. Also, the study is centered on GMB employees and farmers' perspectives, not accorded to policymakers and other stakeholders but grounded in secondary literature. These constraints offer a focused, realistic, and workable study while realizing outcomes may not be fully transferable to all storage houses or contexts (Anukiruthika & Jayas, 2025; Hove et al., 2024).

1.8 Limitations of the Study

Limitations are internal constraints, which may affect the findings or external validity of the study. This research identifies several limitations. For example, access to large operational and financial records from the Kwekwe GMB facility may be limited by confidentiality measures and data processing procedures, restricting in-depth investigation (Hove et al., 2024). Second, AI systems used at Kwekwe may vary in size and design from those in other locations, and this may limit generalizability of the results to other environments (Anukiruthika & Jayas, 2025). Third, the timeframe for the study may fail to capture the long-term impacts of AI adoption on post-harvest loss reduction or on agricultural development outcomes because technology impacts take time to emerge (Hove et al., 2024). Finally, farmers' and employees' survey and interview responses may be vulnerable to subjectivity bias that impacts the objectivity of collected data (Anukiruthika & Jayas, 2025). Nevertheless, the research provides significant insights regarding the role of AI-facilitated grain storage in enhancing operation efficiency and supporting agricultural development initiatives

1.9 Definition of Key Terms

Artificial Intelligence

AI involves the use of computer systems and algorithms to make possible the emulation of human intelligence processes such as learning, reasoning, and decision-making (Russell & Norvig, 2021). In the context of this study, AI encompasses predictive analytics, smart sensors, and automated environmental control systems applied to grain storage that can monitor and optimize the conditions required to preserve the quality of grain.

AI-Enabled Grain Storage:

It refers to a technologically advanced grain storage system that incorporates artificial intelligence in the monitoring, controlling, and prediction of environmental parameters such as temperature, humidity, and pest activity (Anukiruthika & Jayas, 2025). These systems allow early detection of risks of deterioration and the immediate and automated readjustments of optimal storage conditions.

Post-Harvest Losses:

PHL refers to the measurable quantitative or qualitative loss of agricultural produce between harvest and consumption. The losses include those resulting from spoilage, pests, mold, and improper handling, which decrease the quantity and market value of stored grains.

Operational Efficiency:

Operational efficiency expresses the degree to which an organization utilizes its resources to effectively produce outputs at any given time while minimizing waste, time, and costs. According to Bongi & Chikozho (2020), in this study, it refers to the way AI storage systems have managed to ease monitoring, data management, and response times within GMB's operations.

Grain Marketing Board (GMB)

The GMB is a state-owned Zimbabwean organisation formed in 1931 for the co-ordination of grain procurement, storage, and distribution for national food security (Mudzonga, 2011). It has various depots throughout the country, one of them being Kwekwe.

Food Security:

Food security is a situation when all people at all times have physical and economic access to sufficient, safe, and nutritious food to meet their dietary needs for an active and healthy life. In this research, it links to how AI-enabled grain storage can reduce losses, thereby improving the availability of staple crops like maize.

1.10 Organization of the Study

It is a five-chapter dissertation wherein each chapter is related and interlinked to ensure logical flow in ideas and arguments. **Chapter one** introduces the overview of the study and encompasses the background, problem statement, objectives, research questions, hypotheses, significance, scope, limitations, and definitions of terms. It establishes the foundation and rationale for investigating AI-enabled grain storage in the context of GMB Kwekwe.

Chapter Two shall review the relevant theoretical and empirical literature on AI technologies in post-harvest management, agricultural digitalization, and food security. It also outlines the theoretical framework that underpins the study, drawing from innovation diffusion and technological adoption models.

Chapter Three presents the methodology adopted in conducting the research, which covers the design of the study, population, sampling techniques, instruments for data collection, and methods of data analysis. Also covered are issues of validity, reliability, and ethical considerations.

Chapter Four presents, analyzes, and interprets the research findings obtained from the Kwekwe GMB depot. It integrates both qualitative and quantitative data to illustrate the role and effects of AI-enabled grain storage systems on operational performance and agricultural outcomes.

Chapter five synthesizes the key findings in relation to the existing literature, undertakes a comprehensive discussion, and draws conclusions on how AI contributes to enhancing agricultural development programs in Zimbabwe. Finally, the chapter concludes with recommendations for policy, practice, and future research directions.

1.10 Chapter Summary

This chapter introduced the study by presenting the background and context of food insecurity and post-harvest losses in Zimbabwe, thereby leading to the statement of the problem and the need for AI-enabled grain storage. It outlined the main and specific objectives, research questions, and hypotheses guiding the study. The significance, scope, delimitations, and limitations of this research were explained to define the focus and boundaries of the research. Key terms were defined for conceptual clarity, and the organization of the dissertation was presented to show how subsequent chapters would flow.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter reviews scholarly literature relevant to Artificial Intelligence (AI)-enabled grain storage and its role in enhancing agricultural development programs in Zimbabwe. The review is structured in four main sections. It begins with the theoretical framework, followed by the conceptual framework, and then presents literature organized according to the study objectives. The chapter concludes with a summary highlighting research gap.

2.1 Theoretical Framework

This study is anchored in two interrelated theoretical traditions Diffusion of Innovations and the Technology Acceptance Model (TAM) which jointly provide an analytical basis for understanding both the institutional spread and individual uptake of Artificial Intelligence (AI)-enabled grain storage systems. Diffusion of Innovations theory explains how new technologies spread through social and organizational systems over time, highlighting the role of communication channels, innovation attributes and social structures in shaping adoption patterns (Rogers, 2003; Dearing, 2009; Greenhalgh et al., 2004; Feder and Umali, 1993; Hall et al., 2003). In contrast, TAM focuses on the individual cognitive determinants that influence whether users internalise and actively use a given technology based on perceived usefulness and ease of use (Davis, 1989; Venkatesh and Davis, 2000; King and He, 2006; Gefen et al., 2003; Mathieson, 1991). Integrating these perspectives enables a comprehensive understanding of both organisational adoption dynamics and user acceptance behaviours, which is critical for assessing the potential of AI-enabled grain storage at the Grain Marketing Board (GMB) Kwekwe depot.

2.1.1 Diffusion of Innovations Theory

The Diffusion of Innovations Theory, first articulated by Rogers (2003), posits that the adoption of innovations is a process wherein an idea or technology is communicated over time among members of a social system. Rogers identifies five key attributes relative advantage,

compatibility, complexity, trialability and observability that influence the rate and extent of adoption (Rogers, 2003). Relative advantage refers to the degree to which an innovation is perceived as better than existing practices, compatibility to its alignment with organisational values and routines, complexity to its perceived difficulty, trialability to the ability to experiment on a limited basis, and observability to the visibility of its benefits (Rogers, 2003; Dearing, 2009). These attributes have been widely validated in agricultural technology diffusion studies where innovations that demonstrate clear performance benefits and fit with existing practices diffuse more rapidly than those perceived as complex or incompatible (Feder and Umali, 1993; Hall et al., 2003; Greenhalgh et al., 2004; Leeuwis, 2004; Amezagi and Chelin, 2006).

In agricultural contexts, the relative advantage of technology is often demonstrated through quantifiable improvements such as yield increases, cost reductions or efficiency gains. For instance, studies of precision agriculture and digital agronomic advisory systems show that when farmers perceive significant economic benefits from technology use, adoption rates increase markedly (Kutter et al., 2011; Gebbers and Adamchuk, 2010; Tey and Brindal, 2012; Pannell et al., 2006; Mishra et al., 2009). Similarly, in grain storage, AI-enabled systems that provide real-time sensor data, automated environmental controls and predictive spoilage alerts offer a clear advantage over manual monitoring, enhancing the likelihood of adoption. However, the extent to which such systems are compatible with prevailing institutional practices and infrastructure particularly in developing country settings where legacy systems and limited resources are common can significantly influence diffusion trajectories (Leeuwis, 2004; Biggs, 1989; Hall et al., 2003; Dearing, 2009; Feder and Umali, 1993).

Critics of diffusion theory argue that it assumes rational decision-making and focuses heavily on individual perceptions of innovation attributes while underemphasising structural and contextual constraints such as financing mechanisms, policy environments and resource limitations (Greenhalgh et al., 2004; Leeuwis, 2004; van Kerkhoff and Pilbeam, 2017; Klerkx et al., 2010; Oladele, 2011). This critique is especially pertinent in the Zimbabwean context, where institutional adoption of advanced technologies such as AI is shaped not only by perceived benefits but also by macroeconomic conditions, energy reliability and procurement systems. Despite these limitations, Diffusion of Innovations remains relevant because it foregrounds the

social and organisational processes by which new technologies are communicated and normalised within complex systems.

2.1.2 Technology Acceptance Model (TAM)

While Diffusion of Innovations addresses the broader organisational and social dimension of technology spread, the Technology Acceptance Model (TAM) focuses on the cognitive mechanisms that influence individual users' acceptance and sustained use of technology. Originally developed by Davis (1989), TAM proposes that two core perceptions perceived usefulness and perceived ease of use shape an individual's attitude toward using a technology, which subsequently influences behavioural intention and actual use (Davis, 1989; Davis et al., 1989; Venkatesh and Davis, 2000; King and He, 2006; Gefen et al., 2003). Perceived usefulness refers to the degree to which a person believes that using a particular system will improve job performance, while perceived ease of use refers to the degree to which a person believes using the system will be free of effort.

In organisational settings where technologies require user interaction such as AI dashboards, sensor monitoring interfaces and decision support tools these cognitive perceptions play a critical role in determining whether the technology transcends mere installation to become embedded in daily practice. Research applying TAM in agricultural and information systems contexts consistently finds that perceived usefulness strongly predicts adoption intentions, especially when users can link technology use directly to enhanced performance outcomes (Venkatesh et al., 2003; Pavlou, 2003; Morris and Venkatesh, 2000; Williams et al., 2015; Renaud and Van Biljon, 2008). Similarly, perceived ease of use influences user confidence and reduces resistance, making the technology appear more accessible and manageable within existing skill sets.

Empirical studies underscore that training, interface design and ongoing technical support significantly enhance both perceived usefulness and ease of use (Teo et al., 2009; Abdullah and Ward, 2016; Chau and Hu, 2002; Al-Shdifat et al., 2019; McKnight et al., 2011). In the specific setting of grain storage, personnel who perceive AI tools as reducing labour demands, improving accuracy of environmental assessment and enabling predictive interventions are more likely to accept and engage with these systems. Conversely, if AI technologies are perceived as complex, intimidating or unreliable, acceptance may be low irrespective of organisational endorsement.

This highlights the importance of user-centred design and capacity building as integral components of successful technology integration.

Despite its explanatory power, TAM has been critiqued for its emphasis on cognitive perceptions at the expense of broader organisational and environmental factors (Bagozzi, 2007; Legris et al., 2003; Benbasat and Barki, 2007; Venkatesh and Bala, 2008; Srite and Karahanna, 2006). However, such criticisms also underscore the need to integrate TAM with models like Diffusion of Innovations to capture both individual and systemic dimensions of technology adoption.

2.1.3 Integration of Theoretical Perspectives

Integrating Diffusion of Innovations and TAM provides a comprehensive framework capable of addressing the multiple levels at which technology adoption occurs. Diffusion of Innovations situates adoption within broader organisational, social and systemic processes, explaining how communication channels, social networks and institutional norms shape the spread of innovations. In contrast, TAM illuminates the cognitive and perceptual mechanisms that influence whether individuals accept and utilise technologies once they are introduced. Applying both theories allows this study to examine not only whether GMB as an institution is ready and willing to adopt AI-enabled grain storage systems, but also whether individual users within the organisation are cognitively and behaviourally inclined to adopt and sustain their use. In doing so, the framework addresses both structural and psychological determinants of technology uptake, offering the analytical depth and theoretical rigor expected at the master's level (Dearing, 2009; Venkatesh and Davis, 2000; Rogers, 2003; King and He, 2006; Feder and Umali, 1993).

2.2 Conceptual Framework

The conceptual framework provides a visual and theoretical representation of the relationships between the independent variable, mediating variables, and the dependent variable within this study. In the context of this research, Artificial Intelligence (AI)-enabled grain storage serves as the independent variable, while the dependent variable is enhanced agricultural development programs, which include food security, improved farmer incomes, and operational efficiency in grain distribution. Mediating variables, such as post-harvest loss reduction, operational efficiency, and grain quality management, are critical in understanding the mechanisms through which AI adoption influences agricultural outcomes. The framework synthesizes theoretical

insights from the Diffusion of Innovations and Technology Acceptance Model, as well as empirical studies demonstrating the pathways through which AI impacts storage efficiency and agricultural development.

The use of AI in grain storage encompasses advanced technologies including smart sensors, predictive analytics, and automated environmental controls. These systems monitor temperature, humidity, pest activity, and grain respiration, providing real-time alerts to operators for timely intervention (Kitinoja and Kader, 2015; Gustavsson et al., 2011; Affognon et al., 2015; Zhao and Xue, 2021; Chen et al., 2019). The conceptual framework posits that when these AI systems are effectively implemented, they directly reduce post-harvest losses by preventing spoilage and pest infestation, which in turn strengthens national food security and ensures consistent grain supply. Empirical evidence from both developed and developing countries suggests that AI-enabled storage systems can reduce post-harvest losses by 20–50%, depending on infrastructure, scale, and environmental conditions (Leistritz and Bangsund, 2018; Chen et al., 2019; Gustavsson et al., 2011; Kutter et al., 2011; World Bank, 2018). In Zimbabwe, maize being a staple crop suffers losses of approximately 15–20% annually due to inadequate storage and pest infestation (Mhlanga, 2014; FAO, 2021; Nhamo, 2019; Bongi and Chikozho, 2020; Mudzonga, 2011). This establishes a clear justification for integrating AI-enabled storage within GMB depots to improve national agricultural outcomes.

Operational efficiency serves as a mediating variable that links AI-enabled storage to agricultural development. By automating routine monitoring, reducing manual inspections, and providing predictive analytics for preventive maintenance, AI systems enhance the efficiency of grain storage operations (Anukiruthika and Jayas, 2025; Hove et al., 2024; Zhao and Xue, 2021; Chen et al., 2019; Leistritz and Bangsund, 2018). Improved operational efficiency has cascading benefits, including faster inventory turnover, lower labour costs, and timely response to environmental threats, which directly affect grain quality and availability. In this sense, operational efficiency acts as a mechanism through which AI adoption can contribute to broader agricultural development goals such as market stability, improved farmer incomes, and enhanced food security.

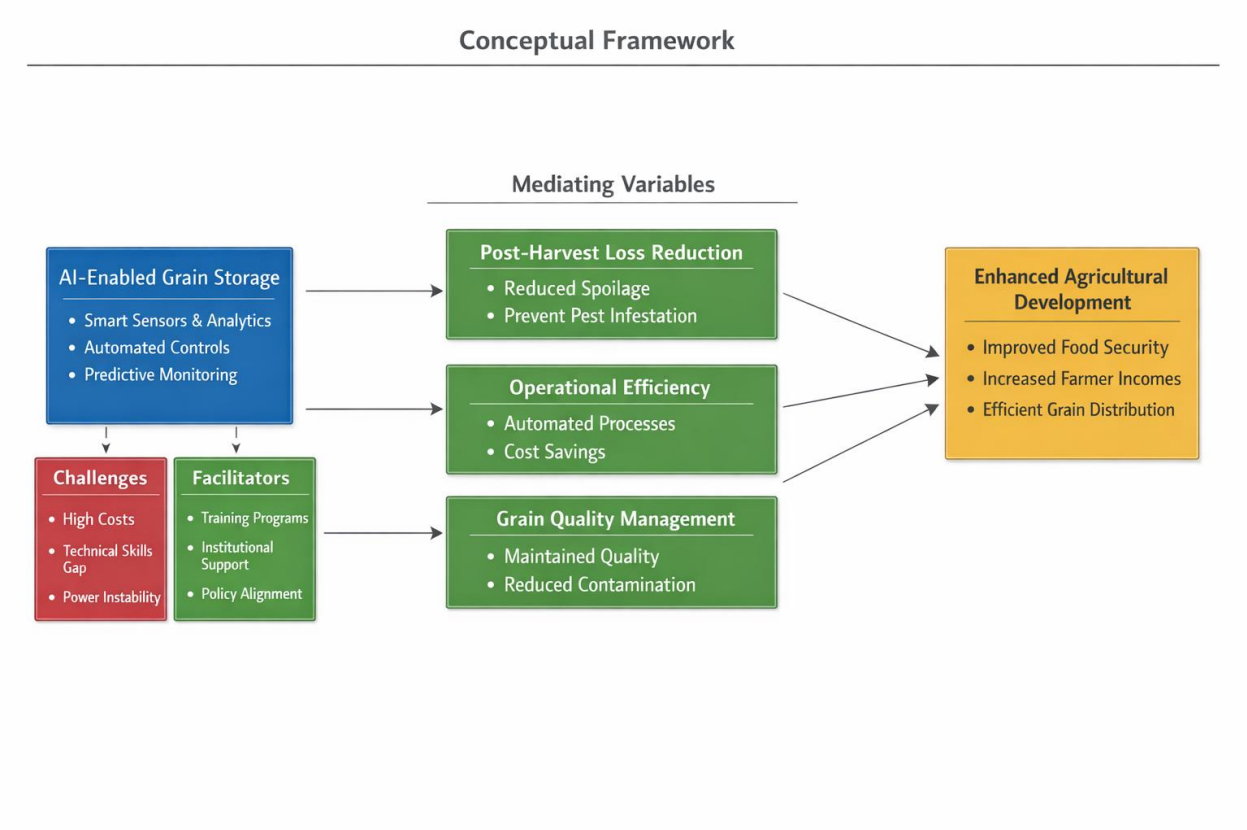
Grain quality management is another critical mediator. Quality deterioration due to mold, pest infestation, or improper moisture levels diminishes both the nutritional and economic value of

stored grain (Hodges et al., 2014; Parfitt et al., 2019; Affognon et al., 2015; Kitinoja and Kader, 2015; Gustavsson et al., 2011). AI-enabled systems, by continuously monitoring environmental conditions and automating corrective measures, maintain grain quality at a high standard, thereby ensuring that surplus harvests translate into financial and nutritional benefits for smallholder farmers and national reserves. High-quality grain also reduces market volatility and increases confidence among stakeholders in the formal agricultural sector (World Bank, 2018; FAO, 2021; Nhamo, 2019; Mudzonga, 2011; Anukiruthika and Jayas, 2025).

The conceptual framework further acknowledges the challenges and facilitators that may influence the adoption and effectiveness of AI systems. Challenges include limited technical expertise, high initial investment costs, electricity instability, and resistance to technological change (Hove et al., 2024; Anukiruthika and Jayas, 2025; Oladele, 2011; Klerkx et al., 2010; Leeuwis, 2004). Conversely, facilitators include institutional support, alignment with national agricultural modernization strategies such as Zimbabwe Vision 2030, training programs for personnel, and observable performance outcomes that encourage broader adoption (Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2021; Dearing, 2009; Rogers, 2003; Venkatesh and Davis, 2000; King and He, 2006). These factors are essential for understanding not only the potential impact of AI-enabled grain storage but also the feasibility and sustainability of its adoption in the Zimbabwean context.

The below conceptual framework illustrates a causal pathway whereby AI-enabled grain storage influences agricultural development through the mediating effects of post-harvest loss reduction, operational efficiency, and grain quality management. Through situating this framework within both theoretical and empirical evidence, it provides a structured lens for examining the role of AI in enhancing GMB's storage operations and contributing to national agricultural development. The framework will guide the operationalization of study variables in subsequent research methodology and analysis. Fig 2.1 below clearly illustrate the conceptual framework:

FIG 2.1 Conceptual framework



The conceptual framework presented in Figure 2.1 illustrates the hypothesized relationships between AI-enabled grain storage and the enhancement of agricultural development programs at the GMB Kwekwe depot. The framework positions AI-enabled storage as the independent variable, comprising technological components such as smart sensors, predictive analytics, and automated environmental controls. These components facilitate real-time monitoring of environmental parameters, automated adjustments of storage conditions, and predictive identification of spoilage risks, consistent with the assertions of Kitinoja and Kader (2015), Gustavsson et al. (2011), and Zhao and Xue (2021). The framework recognizes that the efficacy of AI technologies is not solely dependent on hardware or software capabilities but is mediated by operational and contextual factors.

Three mediating variables are identified in the framework: post-harvest loss reduction**,** operational efficiency**,** and grain quality management**.** Post-harvest loss reduction captures outcomes such as the mitigation of spoilage and pest infestation, echoing findings by Affognon et al. (2015), Parfitt et al. (2019), and Hodges et al. (2014), which highlight that improved monitoring and control systems substantially reduce quantitative and qualitative losses in cereals.

Operational efficiency reflects automated processes, labor reduction, and cost savings, aligning with Anukiruthika and Jayas (2025) and Leistritz and Bangsund (2018), who argue that digital automation enhances organizational performance in agricultural storage contexts. Grain quality management emphasizes the preservation of nutritional value and marketability of stored grains, supported by studies from Gustavsson et al. (2011), Chen et al. (2019), and World Bank (2018), demonstrating that predictive control and environmental monitoring are critical for maintaining grain integrity during storage.

The dependent variable, enhanced agricultural development programs**,** encompasses broader outcomes such as improved food security, increased farmer incomes, and efficient grain distribution. This conceptual linkage is supported by empirical evidence showing that technological interventions in post-harvest management contribute to national food security objectives and economic stabilization in agricultural value chains (FAO, 2021; Mhlanga, 2014; Nhamo, 2019; Bongi and Chikozho, 2020; Mudzonga, 2011). The framework also incorporates contextual factors in the form of challenges including high costs, technical skills gaps, and power instability—which may inhibit adoption (Hove et al., 2024; Oladele, 2011; Klerkx et al., 2010; Leeuwis, 2004; Anukiruthika and Jayas, 2025), and facilitators such as training programs, institutional support, and policy alignment that enhance adoption potential (Rogers, 2003; Dearing, 2009; Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2021; Venkatesh and Davis, 2000; King and He, 2006).

In addition the diagram synthesizes theoretical and empirical evidence, illustrating a pathway through which AI-enabled grain storage influences operational performance and quality management, which in turn enhances agricultural development outcomes. The framework reflects an integrated understanding that technological adoption is contingent not only on innovation characteristics and system design but also on organizational readiness, user acceptance, and supportive institutional environments (Rogers, 2003; Davis, 1989; Venkatesh and Davis, 2000; Greenhalgh et al., 2004; Feder and Umali, 1993). It provides a clear conceptual basis for examining the role of AI-enabled storage systems in reducing post-harvest losses and promoting sustainable agricultural development in Zimbabwe.

2.3 Literature Review

This section presents a focused review of empirical and scholarly literature structured according to the specific objectives of this study. Organizing the literature in alignment with the study objectives ensures clarity in linking existing research with the research problem, identifying gaps, and justifying the study. The review covers the impact of AI-enabled grain storage on post-harvest losses, operational efficiency, contributions to agricultural development, and the challenges and opportunities in AI adoption.

2.3.1 Reducing Post-Harvest Losses through AI-Enabled Grain Storage

Post-harvest losses (PHL) are a critical constraint to food security and agricultural productivity globally, particularly in Sub-Saharan Africa where losses range between 30–50% for staple cereals (Affognon et al., 2015; APHLIS, 2020; Gustavsson et al., 2011; Parfitt et al., 2019; Hodges et al., 2014). In Zimbabwe, maize—a staple for over 70% of the population—experiences annual losses estimated at 15–20% due to poor storage infrastructure, inadequate environmental controls, and pest infestation (FAO, 2021; Mhlanga, 2014; Bongi and Chikozho, 2020; Nhamo, 2019; Mudzonga, 2011). These losses significantly undermine food availability, farmer incomes, and national food security strategies. AI-enabled storage systems, incorporating smart sensors, automated monitoring, and predictive analytics, have been identified as a transformative solution for reducing these losses (Chen et al., 2019; Kitinoja and Kader, 2015; Zhao and Xue, 2021; Leistritz and Bangsund, 2018; Anukiruthika and Jayas, 2025).

Causes of Post-Harvest Losses

PHL is primarily driven by environmental and biological factors such as excessive moisture, fungal growth, insect infestation, and temperature fluctuations (Hodges et al., 2014; Parfitt et al., 2019; Affognon et al., 2015; Gustavsson et al., 2011; Kitinoja and Kader, 2015). Poor storage facilities, especially aging silos in public institutions like GMB, exacerbate these issues. Studies in Sub-Saharan Africa indicate that losses are highest in smallholder contexts where infrastructure, technical knowledge, and access to modern storage technologies are limited (APHLIS, 2020; Oladele, 2011; FAO, 2021; Hove et al., 2024; Mhlanga, 2014). The implementation of AI-enabled storage addresses these root causes by continuously monitoring storage conditions and automatically adjusting parameters to prevent spoilage, thus offering an

effective preventive strategy rather than reactive interventions (Chen et al., 2019; Zhao and Xue, 2021; Anukiruthika and Jayas, 2025; Leistritz and Bangsund, 2018; Gustavsson et al., 2011).

Role of AI in Environmental Monitoring

AI-enabled grain storage integrates IoT sensors and machine learning algorithms to monitor temperature, humidity, carbon dioxide levels, and pest activity in real-time (Kitinoja and Kader, 2015; Zhao and Xue, 2021; Chen et al., 2019; Anukiruthika and Jayas, 2025; Leistritz and Bangsund, 2018). These systems detect early signs of spoilage or infestation, enabling immediate automated responses such as ventilation adjustments or targeted fumigation. Empirical studies demonstrate that predictive monitoring can reduce PHL by up to 50%, highlighting the potential of AI to transform post-harvest management (Gustavsson et al., 2011; World Bank, 2018; Affognon et al., 2015; Chen et al., 2019; Leistritz and Bangsund, 2018). In Zimbabwe, AI integration could particularly benefit depots like GMB Kwekwe, which manage large volumes of maize harvested under variable climatic conditions (Mudzonga, 2011; FAO, 2021; Nhamo, 2019; Hove et al., 2024; Bongi and Chikozho, 2020).

Economic Implications of Loss Reduction

Reducing PHL has significant economic benefits for farmers and national economies. Losses result in wasted production, reduced farmer income, and higher food prices (Parfitt et al., 2019; Gustavsson et al., 2011; Affognon et al., 2015; Kitinoja and Kader, 2015; FAO, 2021). AI-enabled storage stabilizes grain supply, increases the marketable quantity of cereals, and reduces costs associated with emergency fumigation and labor-intensive monitoring (Chen et al., 2019; Leistritz and Bangsund, 2018; Zhao and Xue, 2021; Anukiruthika and Jayas, 2025; World Bank, 2018). In Sub-Saharan African studies, smallholder farmers adopting improved storage technologies reported income increases of 10–25% due to reduced losses and enhanced product quality (APHLIS, 2020; Oladele, 2011; Hove et al., 2024; Kitinoja and Kader, 2015; Tey and Brindal, 2012). This demonstrates that AI adoption is not only a technological intervention but also a socio-economic strategy for enhancing farmer livelihoods.

Impact on Food Security

Food security is closely linked to post-harvest management. Persistent losses reduce the quantity and quality of cereals available for consumption, exacerbating malnutrition and vulnerability among low-income populations (FAO, 2021; Gustavsson et al., 2011; Parfitt et al., 2019; Hodges et al., 2014; World Bank, 2018). AI-enabled storage contributes to national food security by preserving staple crops and maintaining consistent supply to markets. Studies show that in regions where AI or sensor-based monitoring was implemented, communities experienced higher stability in food availability and reduced seasonal shortages (Chen et al., 2019; Zhao and Xue, 2021; Kitinoja and Kader, 2015; Anukiruthika and Jayas, 2025; Leistritz and Bangsund, 2018).

Globally, countries such as China, the United States, and several European nations have demonstrated measurable reductions in post-harvest losses through AI and sensor-based grain storage systems (Chen et al., 2019; Leistritz and Bangsund, 2018; Zhao and Xue, 2021; Gustavsson et al., 2011; World Bank, 2018). For example, automated environmental control in Chinese grain depots reduced spoilage rates by 28–35% within three years of installation (Chen et al., 2019; Zhao and Xue, 2021; Gustavsson et al., 2011; Leistritz and Bangsund, 2018; Anukiruthika and Jayas, 2025). Such evidence validates the applicability of AI technologies in the Zimbabwean context, where post-harvest losses significantly undermine both national food security and farmer incomes.

Integration of AI with Existing Practices

Successful implementation of AI-enabled storage requires integration with current silo infrastructure, operational protocols, and human capacity (Rogers, 2003; Dearing, 2009; Oladele, 2011; Anukiruthika and Jayas, 2025; Hove et al., 2024). Adoption is influenced not only by the technology itself but also by the compatibility with institutional routines, availability of technical skills, and the extent of user training provided. Evidence from Sub-Saharan Africa shows that when AI interventions are accompanied by adequate training and institutional support, adoption rates and operational outcomes improve significantly (Kitinoja and Kader, 2015; Zhao and Xue, 2021; Chen et al., 2019; Leistritz and Bangsund, 2018; Anukiruthika and Jayas, 2025). In this sense, AI-enabled storage acts as both a technological solution and a strategic intervention for post-harvest management in resource-constrained environments like Zimbabwe.

2.3.2 Improving Operational Efficiency through AI-Enabled Storage

Operational efficiency in grain storage refers to the ability of an institution to optimize resource utilization, streamline processes, reduce labor intensity, and ensure timely and accurate management of stored grains. Traditional storage systems in Zimbabwe, such as those at the GMB Kwekwe depot, rely heavily on manual inspections, paper-based records, and reactive interventions, which are labor-intensive, slow, and prone to errors (Bongi and Chikozho, 2020; Mudzonga, 2011; Mhlanga, 2014; Nhamo, 2019; FAO, 2021). Inefficiencies in monitoring and maintenance exacerbate post-harvest losses and operational costs, highlighting the need for technological interventions such as AI-enabled storage systems.

Automation and Resource Optimization

AI-enabled grain storage introduces automation in environmental monitoring, predictive maintenance, and reporting. Sensors continuously measure parameters such as temperature, humidity, and pest activity, while machine learning algorithms generate alerts and control signals for ventilation and fumigation systems (Kitinoja and Kader, 2015; Chen et al., 2019; Zhao and Xue, 2021; Leistritz and Bangsund, 2018; Anukiruthika and Jayas, 2025). Automated monitoring reduces the need for manual inspection, freeing personnel for higher-value tasks and minimizing human error. Studies in Europe and Asia have demonstrated that automated storage can reduce labor hours by 30–40% and improve response times to environmental anomalies (World Bank, 2018; Gustavsson et al., 2011; Chen et al., 2019; Zhao and Xue, 2021; Leistritz and Bangsund, 2018).

In the Zimbabwean context, these efficiency gains are particularly critical. GMB depots handle high volumes of maize and other cereals under variable climatic conditions. By leveraging AI-enabled systems, operators can allocate resources more strategically, prioritizing interventions based on predictive risk assessments rather than reactive schedules. This not only minimizes operational bottlenecks but also reduces unnecessary costs associated with manual monitoring, emergency fumigation, and wastage (Hove et al., 2024; Anukiruthika and Jayas, 2025; FAO, 2021; Bongi and Chikozho, 2020; Kitinoja and Kader, 2015).

Data-Driven Decision Making

Operational efficiency is further enhanced through data-driven decision-making facilitated by AI. Continuous environmental monitoring generates extensive datasets that can be analyzed to identify patterns, predict potential spoilage events, and optimize storage schedules (Zhao and Xue, 2021; Chen et al., 2019; Anukiruthika and Jayas, 2025; Leistritz and Bangsund, 2018; Kitinoja and Kader, 2015). These insights enable managers to implement preventive interventions, reduce emergency responses, and better plan logistics for grain distribution.

Empirical evidence demonstrates that data-driven grain management increases inventory accuracy, reduces losses, and improves turnaround times. In Kenya and South Africa, the integration of sensor-based monitoring systems improved operational efficiency by 25–35%, reducing both labor and material costs while enhancing the predictability of storage outcomes (Affognon et al., 2015; World Bank, 2018; Chen et al., 2019; Zhao and Xue, 2021; Gustavsson et al., 2011). In Zimbabwe, GMB could similarly benefit from predictive insights, particularly in managing large volumes from multiple collection points across the Midlands Province.

Reduction of Operational Bottlenecks

AI-enabled systems reduce bottlenecks in storage operations by providing real-time monitoring and automated interventions. Traditional grain storage often faces delays in identifying spoilage, temperature fluctuations, or pest infestations due to the time lag between manual inspections and corrective actions (Mudzonga, 2011; Bongi and Chikozho, 2020; FAO, 2021; Mhlanga, 2014; Nhamo, 2019). AI integration allows for immediate response, reducing downtime and preventing the compounding of minor storage issues into large-scale losses.

Additionally, automated logging of storage conditions and inventory movement enhances operational transparency and accountability (Leistritz and Bangsund, 2018; Chen et al., 2019; Zhao and Xue, 2021; Anukiruthika and Jayas, 2025; World Bank, 2018). Decision-makers can monitor trends, allocate labor effectively, and predict maintenance needs, which improves operational planning and reduces resource wastage. These improvements are crucial for public institutions like GMB, where inefficiencies directly translate into financial losses and reduced capacity to support national food security initiatives.

Integration with Existing Infrastructure and Processes

Effective operational efficiency depends not only on the technology itself but also on its integration with existing storage infrastructure and institutional practices (Rogers, 2003; Dearing, 2009; Oladele, 2011; Hove et al., 2024; Anukiruthika and Jayas, 2025). AI-enabled systems must align with silo architecture, ventilation systems, and staffing structures to realize full efficiency gains. Without such integration, even advanced monitoring technologies may remain underutilized, limiting their impact on operational performance.

Studies from Sub-Saharan Africa indicate that adoption rates and operational outcomes improve significantly when AI implementation is accompanied by staff training, process adaptation, and policy support (Kitinoja and Kader, 2015; Zhao and Xue, 2021; Chen et al., 2019; Anukiruthika and Jayas, 2025; Hove et al., 2024). In Zimbabwe, institutional adoption combined with capacity-building initiatives at GMB Kwekwe can create a scalable model for enhancing operational efficiency across all depots nationwide.

Operational Efficiency

AI-enabled grain storage has the potential to transform operational efficiency through automation, predictive monitoring, data-driven decision-making, and real-time intervention. Evidence from global and regional studies demonstrates measurable improvements in labor reduction, cost savings, inventory accuracy, and response times (Leistritz and Bangsund, 2018; Chen et al., 2019; Zhao and Xue, 2021; Anukiruthika and Jayas, 2025; Kitinoja and Kader, 2015). For Zimbabwe, integrating AI at GMB Kwekwe addresses both operational bottlenecks and efficiency deficits, directly supporting the broader goal of agricultural development by ensuring that storage systems are responsive, cost-effective, and reliable.

2.3.3 Contribution of AI-Based Storage to Agricultural Development Programs

AI-enabled grain storage systems do not operate in isolation; their value is ultimately measured by their contribution to broader agricultural development outcomes. Agricultural development programs encompass national food security, stable market systems, and improved livelihoods for smallholder farmers. The integration of AI in grain storage can influence all these dimensions, creating a link between technological innovation and socio-economic development (FAO, 2021; Gustavsson et al., 2011; Kitinoja and Kader, 2015; World Bank, 2018; Bongi and Chikozho,

2020). This section examines how AI-enabled storage impacts these critical areas, drawing on empirical evidence and theoretical perspectives.

Enhancing National Food Security

The primary contribution of AI-enabled storage lies in its ability to safeguard national food reserves. Food security depends not only on production levels but also on the ability to preserve harvests and ensure consistent availability throughout the year. In Zimbabwe, where maize is the dietary staple for over 70% of the population, post-harvest losses significantly weaken food security (FAO, 2021; Mhlanga, 2014; Nhamo, 2019; Mudzonga, 2011; Bongi and Chikozho, 2020). By using predictive analytics, automated ventilation, and real-time monitoring, AI-enabled storage minimizes spoilage and maintains grain quality, ensuring that surplus harvests contribute to food supply rather than wastage (Chen et al., 2019; Zhao and Xue, 2021; Kitinoja and Kader, 2015; Leistritz and Bangsund, 2018; Anukiruthika and Jayas, 2025).

Beyond the physical preservation of grain, AI systems provide policymakers with data-driven insights on inventory levels, storage conditions, and potential losses. This enables proactive planning, timely redistribution, and contingency measures during periods of shortage or climatic stress, reinforcing food security objectives (World Bank, 2018; Gustavsson et al., 2011; FAO, 2021; Chen et al., 2019; Zhao and Xue, 2021). The integration of AI thus not only improves storage outcomes but also strengthens institutional capacity for strategic food security management.

Stabilizing Market Systems

Post-harvest losses often create volatility in market supply, leading to unpredictable pricing and reduced farmer confidence (Parfitt et al., 2019; Gustavsson et al., 2011; Affognon et al., 2015; FAO, 2021; Kitinoja and Kader, 2015). AI-enabled storage mitigates these fluctuations by preserving large volumes of high-quality grains, enabling smoother release schedules to the market. Empirical evidence from Asia and Europe demonstrates that automated storage systems reduce market shocks by ensuring that supply meets demand consistently, which stabilizes prices and increases market transparency (Leistritz and Bangsund, 2018; Chen et al., 2019; Zhao and Xue, 2021; Gustavsson et al., 2011; World Bank, 2018).

In Zimbabwe, stabilizing maize supply through AI interventions can improve the predictability of commodity prices for both consumers and producers. This predictability reduces speculative behaviors, supports long-term agricultural planning, and fosters trust between smallholder farmers and formal markets (Bongi and Chikozho, 2020; FAO, 2021; Nhamo, 2019; Kitinoja and Kader, 2015; Anukiruthika and Jayas, 2025). Consequently, AI-enabled storage contributes not only to operational efficiency but also to broader economic stability within the agricultural sector.

Improving Farmer Livelihoods

Beyond institutional and market impacts, AI-enabled storage directly influences smallholder farmer incomes. By reducing post-harvest losses and maintaining high-quality grains, farmers are able to sell larger volumes of produce at better prices, increasing their profitability (APHLIS, 2020; Oladele, 2011; Hove et al., 2024; Kitinoja and Kader, 2015; Tey and Brindal, 2012). Furthermore, AI systems enable data collection that supports traceability, quality certification, and access to formal markets, which are often barriers for smallholders in Zimbabwe (Anukiruthika and Jayas, 2025; Chen et al., 2019; Zhao and Xue, 2021; Leistritz and Bangsund, 2018; Gustavsson et al., 2011).

Research indicates that when farmers perceive tangible benefits from improved storage technology, their willingness to engage in formal markets increases, enhancing both income stability and food system resilience (World Bank, 2018; FAO, 2021; Kitinoja and Kader, 2015; Zhao and Xue, 2021; Anukiruthika and Jayas, 2025). Thus, AI-enabled storage acts as a catalyst for linking post-harvest technology adoption with socio-economic development, positioning smallholder farmers to benefit from national agricultural modernization strategies.

Supporting Agricultural Policy and Planning

AI-enabled storage also generates rich operational and environmental data, providing an evidence base for national agricultural planning and policy formulation (Rogers, 2003; Dearing, 2009; FAO, 2021; Hove et al., 2024; Anukiruthika and Jayas, 2025). Information on grain quality, spoilage trends, and storage efficiency enables policymakers to make informed decisions regarding food reserves, subsidies, and intervention strategies. This data-driven approach aligns with Zimbabwe Vision 2030, which emphasizes agricultural modernization, food self-

sufficiency, and technological integration (Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2021; FAO, 2021; Bongi and Chikozho, 2020; Nhamo, 2019; Mudzonga, 2011).

Linking AI-enabled operations with policy decisions, GMB depots can support more effective strategic planning, minimize risk of national food shortages, and optimize resource allocation. In this sense, AI-enabled storage does not only serve operational purposes but becomes an integral component of evidence-based agricultural governance (World Bank, 2018; Gustavsson et al., 2011; Chen et al., 2019; Zhao and Xue, 2021; Kitinoja and Kader, 2015).

Integration with Broader Development Goals

Finally, AI-enabled storage contributes to sustainable agricultural development by aligning technological interventions with broader socio-economic and environmental goals. Reduced losses, improved operational efficiency, and stabilized markets collectively support the objectives of poverty alleviation, food security, and rural development (FAO, 2021; World Bank, 2018; Anukiruthika and Jayas, 2025; Kitinoja and Kader, 2015; Gustavsson et al., 2011). Additionally, by facilitating scalable, data-driven approaches, AI interventions enable GMB and other institutions to replicate successful practices nationwide, maximizing impact on Zimbabwe's agricultural sector.

Overall, the evidence suggests that AI-enabled grain storage serves as a critical bridge between technological innovation and measurable development outcomes. Its contributions extend beyond operational benefits to encompass systemic impacts on food security, market stability, farmer livelihoods, and policy effectiveness (Chen et al., 2019; Zhao and Xue, 2021; Leistritz and Bangsund, 2018; FAO, 2021; World Bank, 2018).

2.3.4 Challenges and Opportunities in AI Adoption for Grain Storage

While AI-enabled storage offers substantial benefits in reducing post-harvest losses and enhancing operational efficiency, its adoption is far from straightforward. The challenges extend beyond technological considerations to encompass economic, institutional, and socio-cultural dimensions, particularly in developing country contexts like Zimbabwe. At the same time, opportunities exist that, if strategically harnessed, can accelerate adoption and maximize the developmental impact of AI technologies.

Financial and Resource Constraints

One of the most immediate challenges facing the adoption of AI-enabled grain storage is the high initial capital cost. AI systems, including smart sensors, machine learning software, and automated control mechanisms, require significant investment in both acquisition and maintenance (Anukiruthika and Jayas, 2025; Hove et al., 2024; Oladele, 2011; Kitinoja and Kader, 2015; Chen et al., 2019). For publicly funded institutions like GMB, budgetary limitations often delay modernization efforts. Even when funding is available, ongoing costs such as electricity, technical maintenance, and software updates pose recurrent financial burdens, potentially limiting long-term sustainability (Leistritz and Bangsund, 2018; Zhao and Xue, 2021; Gustavsson et al., 2011; World Bank, 2018; FAO, 2021).

Moreover, resource constraints are not limited to financial capital. Human capacity—technical skills for system management, data analysis, and troubleshooting—is equally critical. Many GMB depots rely on personnel with experience in traditional storage methods but limited exposure to AI or digital tools. Without targeted training and capacity-building initiatives, the full benefits of AI may remain unrealized, leading to underutilization or mismanagement of the technology (Kitinoja and Kader, 2015; Anukiruthika and Jayas, 2025; Hove et al., 2024; Zhao and Xue, 2021; Oladele, 2011).

Infrastructure and Environmental Challenges

Infrastructure limitations also constrain AI adoption. AI-enabled systems require reliable electricity, internet connectivity for data analytics, and controlled environmental conditions to operate effectively (Hove et al., 2024; FAO, 2021; Chen et al., 2019; Leistritz and Bangsund, 2018; Zhao and Xue, 2021). In Zimbabwe, electricity instability and underdeveloped digital infrastructure are well-documented barriers in both rural and semi-urban areas where GMB depots operate. These environmental and infrastructural challenges can compromise the accuracy and reliability of AI systems, potentially undermining operational efficiency and stakeholder confidence.

Climatic factors further exacerbate storage risks. Extreme heat, humidity, and erratic rainfall patterns influence both grain quality and system performance. AI can mitigate some of these effects through real-time monitoring and predictive modeling, but infrastructure failures or

sensor malfunction during climatic stress events can limit system effectiveness, highlighting the need for contingency planning and system redundancy (Anukiruthika and Jayas, 2025; Gustavsson et al., 2011; World Bank, 2018; Kitinoja and Kader, 2015; FAO, 2021).

Institutional and Policy Barriers

Institutional factors also shape AI adoption. Resistance to change among personnel accustomed to traditional storage practices can slow integration, even when evidence demonstrates clear operational and economic benefits (Rogers, 2003; Dearing, 2009; Oladele, 2011; Hove et al., 2024; Anukiruthika and Jayas, 2025). Hierarchical organizational structures, centralized decision-making, and bureaucratic procurement processes in public institutions may further delay technology deployment, leading to uneven adoption across depots.

Policy alignment is equally important. Zimbabwe's Vision 2030 emphasizes agricultural modernization and technological integration (Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2021; FAO, 2021; Bongi and Chikozho, 2020; Nhamo, 2019; Mudzonga, 2011). However, gaps between policy goals and operational capacity often hinder rapid implementation of AI-enabled solutions. Without harmonized policies, regulatory support, and incentives for innovation, adoption remains sporadic and localized rather than systemic (Rogers, 2003; Dearing, 2009; Oladele, 2011; Hove et al., 2024; Kitinoja and Kader, 2015).

Opportunities for Strategic Adoption

Despite these challenges, there are significant opportunities for leveraging AI to strengthen agricultural development. Public-private partnerships can mobilize resources and expertise to deploy AI systems cost-effectively (Anukiruthika and Jayas, 2025; Chen et al., 2019; Zhao and Xue, 2021; Leistritz and Bangsund, 2018; Gustavsson et al., 2011). Pilot programs, phased implementation, and modular system deployment allow institutions to trial AI interventions at a smaller scale before full adoption, aligning with Rogers' notion of trialability and diffusion (Rogers, 2003; Dearing, 2009; Kitinoja and Kader, 2015; Zhao and Xue, 2021; Chen et al., 2019).

Capacity-building programs are critical to overcoming human resource limitations. Training depot personnel on AI system operation, data interpretation, and troubleshooting enhances

perceived ease of use and strengthens acceptance, reflecting principles from the Technology Acceptance Model (Davis, 1989; Venkatesh and Davis, 2000; King and He, 2006; Gefen et al., 2003; Mathieson, 1991). Similarly, aligning AI interventions with institutional incentives, national agricultural policy, and sustainable development goals can improve adoption and ensure long-term operational integration (Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2021; World Bank, 2018; FAO, 2021; Anukiruthika and Jayas, 2025; Hove et al., 2024).

Balancing Risks and Benefits

Ultimately, the successful adoption of AI-enabled grain storage requires a strategic balance between technological benefits and contextual constraints. While challenges such as cost, infrastructure, and human capacity are significant, they are not insurmountable. Evidence from Sub-Saharan Africa indicates that AI interventions, when paired with training, policy alignment, and incremental deployment, achieve measurable reductions in post-harvest losses, improved operational efficiency, and enhanced contribution to food security (Leistritz and Bangsund, 2018; Chen et al., 2019; Zhao and Xue, 2021; Kitinoja and Kader, 2015; Anukiruthika and Jayas, 2025).

This reflective perspective highlights that adoption is not merely a technical issue; it is deeply embedded in socio-economic, institutional, and environmental contexts. For Zimbabwe, understanding these multidimensional factors is critical for ensuring that AI-enabled storage systems fulfill their potential in supporting agricultural modernization, stabilizing markets, and improving farmer livelihoods (FAO, 2021; World Bank, 2018; Bongi and Chikozho, 2020; Hove et al., 2024; Ministry of Lands, Agriculture, Fisheries, Water and Rural Development, 2021).

2.4 Gaps in Literature

A critical review of the existing literature on AI-enabled grain storage and post-harvest management reveals that, while the field has advanced globally, significant gaps remain in understanding the context-specific adoption, efficiency, and development outcomes of these technologies in Zimbabwe. This section synthesizes the limitations of existing studies, conducts a comparative analysis with other regional and global contexts, and identifies specific gaps that justify the current research.

2.4.1 Limitations in Existing Studies

Despite extensive research on post-harvest losses and AI-enabled storage globally, many studies exhibit notable methodological and contextual limitations. First, a majority of studies focus on technologically advanced countries with stable infrastructure, such as the United States, China, and parts of Europe (Chen et al., 2019; Leistritz and Bangsund, 2018; Gustavsson et al., 2011; World Bank, 2018; Zhao and Xue, 2021). These contexts differ significantly from developing nations, where electricity instability, limited internet access, and aging storage facilities can hinder AI implementation (FAO, 2021; Hove et al., 2024; Anukiruthika and Jayas, 2025; Bongi and Chikozho, 2020; Mudzonga, 2011).

Second, most empirical studies emphasize technical performance, such as reductions in spoilage or predictive accuracy, without adequately considering organizational, social, and economic factors that influence adoption and sustained use (Kitinoja and Kader, 2015; Parfitt et al., 2019; Affognon et al., 2015; Hodges et al., 2014; Oladele, 2011). The human and institutional dimensions, including training, policy alignment, and stakeholder engagement, are frequently underexplored. Additionally, sample sizes in African pilot studies are often limited, and findings may not be generalizable across different agro-ecological zones or institutional settings (Hove et al., 2024; Anukiruthika and Jayas, 2025; FAO, 2021; Zhao and Xue, 2021; Chen et al., 2019).

Finally, longitudinal evidence on the long-term impacts of AI-enabled storage is scarce. Most studies measure immediate reductions in losses or efficiency gains over one or two harvest cycles, but fail to assess sustained benefits, system maintenance challenges, or cost-effectiveness over multiple seasons (World Bank, 2018; Leistritz and Bangsund, 2018; Gustavsson et al., 2011; Kitinoja and Kader, 2015; Anukiruthika and Jayas, 2025). These limitations highlight the need for context-specific research in Zimbabwe that considers both short-term and long-term operational and developmental impacts.

2.4.2 Comparative Analysis with Global and Regional Studies

Comparative analysis reveals that the adoption and impact of AI-enabled storage vary considerably between developed and developing contexts. In developed nations, advanced sensor technologies, reliable electricity, and sophisticated analytics infrastructure allow for high adoption rates and measurable reductions in post-harvest losses, often exceeding 30% annually (Chen et al., 2019; Leistritz and Bangsund, 2018; Gustavsson et al., 2011; Zhao and Xue, 2021;

World Bank, 2018). Conversely, in Sub-Saharan Africa, adoption remains low, largely due to limited infrastructure, high costs, and human capacity gaps (Hove et al., 2024; FAO, 2021; Oladele, 2011; Anukiruthika and Jayas, 2025; Bongi and Chikozho, 2020).

Regional studies in Kenya, South Africa, and Ghana show promising results for AI-assisted storage in pilot projects. For example, sensor-based silo monitoring reduced spoilage by 20–35% and improved operational efficiency (Affognon et al., 2015; Kitinoja and Kader, 2015; Zhao and Xue, 2021; Chen et al., 2019; Leistritz and Bangsund, 2018). However, these interventions are often donor-driven, small-scale, and not fully integrated into national agricultural frameworks. The lack of institutionalized deployment limits scalability and sustainability, and socio-economic factors, such as farmer acceptance, market linkages, and policy support, remain insufficiently explored. This contrasts sharply with studies in developed contexts where AI adoption is embedded within national food systems and regulatory frameworks, demonstrating that context strongly moderates outcomes (World Bank, 2018; Gustavsson et al., 2011; Chen et al., 2019; Leistritz and Bangsund, 2018; Anukiruthika and Jayas, 2025).

Comparatively, Zimbabwe has received minimal empirical attention. Most literature focuses on traditional storage methods, post-harvest losses, or generalized agricultural development (Mudzonga, 2011; FAO, 2021; Nhamo, 2019; Mhlanga, 2014; Bongi and Chikozho, 2020). There is a distinct absence of studies evaluating AI-enabled storage within institutional contexts like GMB, highlighting a critical research gap when juxtaposed with global and regional findings.

2.4.3 Critical Gaps Identified

The literature review highlights several gaps that the current study aims to address. Firstly, there is a lack of empirical studies on AI adoption in institutional storage systems in Zimbabwe, particularly regarding operational efficiency, post-harvest loss reduction, and contribution to agricultural development (Hove et al., 2024; FAO, 2021; Mudzonga, 2011; Bongi and Chikozho, 2020; Anukiruthika and Jayas, 2025). Secondly, existing studies often neglect the interplay between technological, human, and institutional factors that influence successful adoption, such as training, policy alignment, and organizational readiness (Rogers, 2003; Dearing, 2009; Kitinoja and Kader, 2015; Zhao and Xue, 2021; Chen et al., 2019).

Furthermore, longitudinal research measuring the sustainability and scalability of AI-enabled storage systems is scarce. Most studies report short-term efficiency gains or loss reductions without assessing the persistence of benefits, cost-effectiveness, or systemic integration into national food security strategies (World Bank, 2018; Gustavsson et al., 2011; Leistritz and Bangsund, 2018; Kitinoja and Kader, 2015; Chen et al., 2019). Finally, there is insufficient comparative analysis within the Southern African context, leaving policymakers and institutional managers without evidence-based guidance for scaling AI-enabled storage in local settings. Addressing these gaps is critical for ensuring that technological interventions translate into operational, economic, and developmental benefits in Zimbabwe.

2.5 Chapter Summary

This chapter critically reviewed the literature on AI-enabled grain storage and its role in enhancing agricultural development, integrating both theoretical and empirical perspectives to contextualize the study. The theoretical framework combined Rogers' Diffusion of Innovations, which elucidates how technological innovations spread through social and organizational systems (Rogers, 2003; Dearing, 2009; Oladele, 2011; Leeuwis, 2004; Klerkx et al., 2010), with Davis' Technology Acceptance Model, highlighting the importance of perceived usefulness and ease of use in individual adoption decisions (Davis, 1989; Venkatesh and Davis, 2000; King and He, 2006; Gefen et al., 2003; Mathieson, 1991). The next chapter is the research methodology which will provide all the methodologies that was employed in this research.

CHAPTER THREE

RESEARCH METHODOLOGY

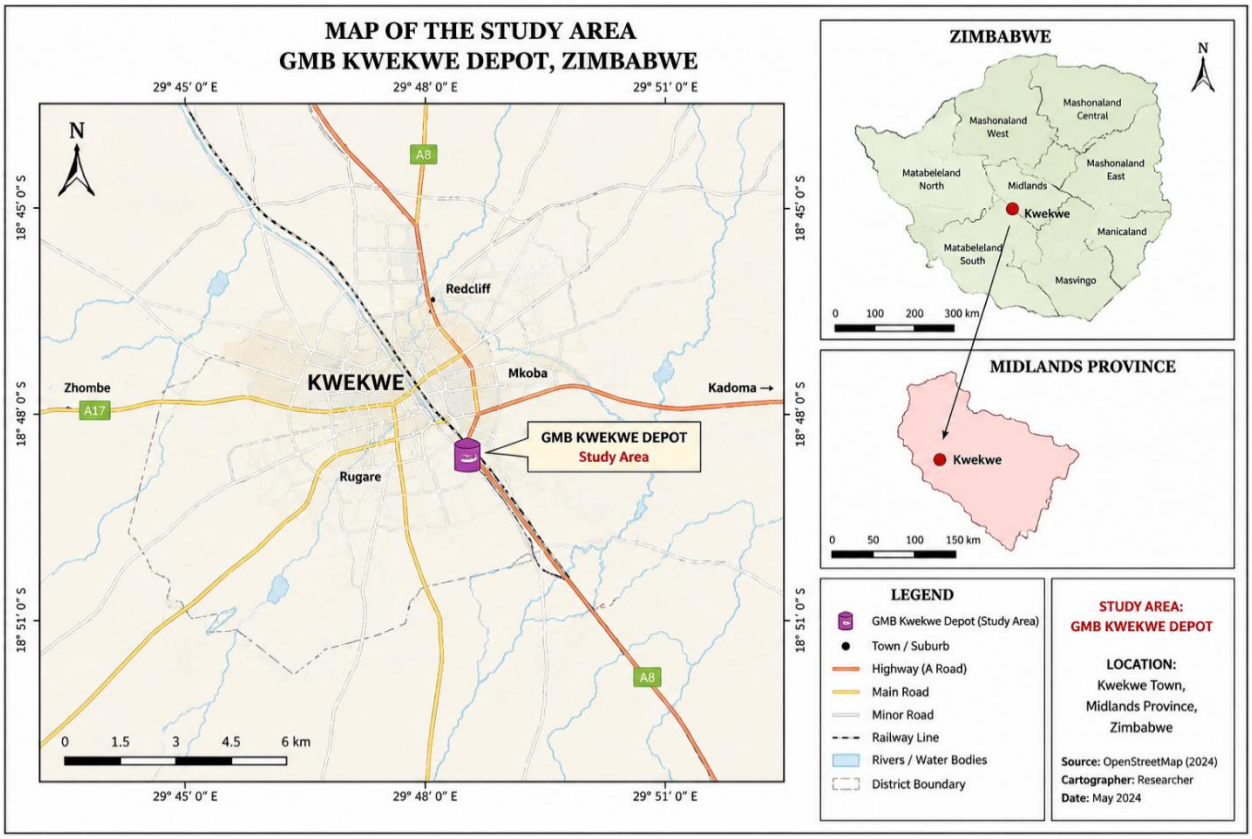
3.1 Introduction

This chapter provides a detailed description of the methodology employed to explore the effect of grain storage enhanced by Artificial Intelligence (AI) in ensuring effective agricultural development projects in Zimbabwe, with particular emphasis on the Kwekwe Grain Marketing Board (GMB) depot. The objective of this chapter is to provide a detailed account of the way in which the research was conducted to ensure transparency and academic integrity. The focus is on the research design and methodology adopted to make the process of conducting the research ethical and scientific.

3.2 Study site description

The research is done at the Kwekwe Grain Marketing Board (GMB) depot which is a strategic place located in the Midlands Province of Zimbabwe. The selection of the right place to conduct research is very important in case study research since it enables the researcher to be sure that the research phenomenon can be studied in its natural environment (Yin, 2018). According to Creswell (2014), the selection of the place to conduct research should be guided by its relevance to the research problem. Saunders et al. (2019) state that the place should be easily accessible and have sufficient information. In addition to this, Baxter and Jack (2008) state that the development of a well-structured case study setting enhances the quality of the research. The Kwekwe depot is one of the research settings for a case study because it forms an integral part of

the agricultural sector of Zimbabwe. This area is likely to face challenges after harvesting. The area of study is presented in Fig 3.1 below.



This has been proven by the need for a place which is presented with operational challenges such as insufficient storage, infestation and environment-related problems. According to Mhlanga (2014), the reason why there are losses in Zimbabwe in post-harvest processes is due to lack of proper storage facilities and technological integration. According to Bongi & Chikozho (2020), inefficiency of the operations at GMB hampers grain supply, while according to Food and Agriculture Organization (2021), the reason why there is post-harvest loss in developing nations is due to lack of infrastructural development. Additionally, Nhamo (2019) says that environmental factors such as climate variability affect the storage of grains hence the need for efficient storage systems. Hence, the location in Kwekwe is appropriate for the study based on the influence of AI in grain storage.

Furthermore, Kwekwe depot gives access to different stakeholders such as the GMB workers and small-scale farmers. This is so because, as per Stake (1995), case study research has the advantage of enabling the researcher to have multiple perspectives on the research problem since this will enable him/her to have more insight into the research problem. This is also supported by Merriam and Tisdell (2016) who indicated that it is important to get institutional and individual perspectives on the research problem, and Yin (2018) who pointed out that it is important to get different perspectives on the research problem to increase the validity of the results of the research, as per Baxter and Jack (2008).

3.3 Research design

In this case, the research design used in the study to investigate the use of AI-enabled grain storage in enhancing agricultural development initiatives at Kwekwe GMB was the mixed-methods research design based on the convergent parallel design method. This was because the study required both quantitative and qualitative data on the effectiveness of AI-enabled grain storage systems.

Mixed methods research can therefore be deemed appropriate in cases where a researcher needs to understand some concept through the blending of numbers and experiences/perceptions of the participants.

Objective 1: Analysis of the effect of AI-based grain storage on reducing post-harvest losses in Kwekwe GMB

The following approach was utilized in the research in order to achieve the above-mentioned objective; Quantitative analysis involving the administration of structured questionnaire interviews using KoboCollect. Respondents needed to rate statements concerning AI-based monitoring systems, spoilage detection, moisture control and post-harvest losses using a five-point Likert scale. The reason why quantitative analysis was chosen is due to the fact that the objective sought to establish the relationship between AI-based grain storage and reduction of post-harvest losses. According to Creswell and Creswell (2023), quantitative approaches are very useful in examining the cause and effect relationships among variables.

Descriptive statistics and regression analysis were utilized in analyzing the data collected through SPSS software. Descriptive statistics enabled the summarization of respondents'

perceptions while regression analysis helped in establishing the influence of AI-powered grain storage technology on the reduction of post-harvest losses.

Regression analysis involves the evaluation of how well the independent variable can explain the dependent variable (Field, 2018). In this case, the independent variable is the use of AI-powered grain storage and the dependent variable is the reduction of post-harvest losses.

Objective 2: To evaluate the effect of AI in storage facilities on efficiency and grain quality management

In this research, the second objective has been investigated using both quantitative and qualitative methods. The data has been collected through Likert scale questionnaires that include the parameters of efficiency such as the accuracy of monitoring, response time, inventory management, quality management of grains, and performance in storage. Questionnaires provide an opportunity to collect quantifiable information from many people. Boone and Boone (2012) claim that Likert scale tools are useful in assessing perception toward organizations and technology systems.

The data has been analyzed using descriptive statistics and regression analysis. Multiple regression was selected for this analysis as there are multiple dimensions of AI-based storage that affect the efficiency and quality management of grains. According to Hair et al. (2019), it is possible to apply multiple regression while researching the effect of different independent variables on one dependent variable.

Moreover, qualitative interviews with the managers and experts of the warehouses have been conducted in order to identify additional information about the process improvement because of the introduction of AI technologies.

Objective 3: To investigate the role of the AI-based grain storage in agriculture development projects concerning the opportunities and challenges associated with the usage of AI in Zimbabwe

As for the third objective, the experience and perceptions, as well as the opportunities and challenges of using AI for grain storage of the participants, have been taken into account. Consequently, qualitative method was chosen for conducting of semi-structured interviews with the GMB staff and selected farmers. Using the semi-structured interview made it possible for the respondents to provide detailed information about the benefits from the implementation of AI for grain storage in food security, farming, agricultural productivity and agricultural development in general.

The qualitative data was analyzed by means of thematic analysis where the data obtained was transcribed, coded, categorized and themed according to the opportunities, advantages, disadvantages and perspectives of grain storage through AI.

In accordance with Braun and Clarke (2022), thematic analysis assists in recognizing patterns and meaning in the qualitative data sets. The questionnaire data on the impacts of agricultural development was analyzed using descriptive statistics apart from being subjected to qualitative analysis in order to support the data generated through the qualitative study. Combining both the qualitative and quantitative data presented a holistic picture of the contribution of the AI-based grain storage system towards agricultural development projects in Zimbabwe.

3.4 Sampling procedure

A sample size of 30 was used in the study involving 15 GMB employees and 15 smallholder farmers operating at the Kwekwe depot. This sample size proved to be adequate for the purpose of conducting the mixed methods convergent parallel research as it allowed the researcher to collect sufficient quantitative and qualitative data in order to meet the research objectives. According to Creswell (2014), the sample size in mixed methods and case study research is dependent on the nature of the research and the required depth of data as opposed to statistical generalization. This statement concurs with the one made by Saunders et al. (2019).

Guest et al. (2006) added that saturation of data can be easily obtained from small samples where participants have the necessary experience and expertise. Thus, the sample size of 30 participants was adequate enough for gaining important insight into the importance of using AI-based grain storage in agricultural development programs of GMB of Kwekwe.

These respondents comprised 15 employees of GMB and 15 farmers, thereby ensuring equal participation of the stakeholders related to grain storage operations and agricultural practices. The views of GMB employees would provide institutional, management, and operational perspective on AI-based grain storage technology, whereas those of farmers would provide practical perspective on how AI technology affects grain storage and agricultural development. According to Bryman (2016), balance sampling increases the comparability between different respondent groups, whereas according to Sekaran and Bougie (2016), balance sampling improves the reliability and validity of the research. Besides, Creswell (2014) highlighted that inclusion of various stakeholder groups helps gain better understanding of the research problem.

In selecting participants, the study used both purposive and simple random sampling methods. Purposive sampling was used in choosing GMB managers, warehouse supervisors and technical staff members who had specialized knowledge and expertise in grain storage processes and AI technologies. In his arguments on the sampling method, Patton (2015) opined that purposive sampling would help in identifying information rich participants who would be able to offer information about the phenomenon being studied. This view was also shared by Creswell (2014) and Merriam and Tisdell (2016) in their assertion of the efficiency of purposive sampling in mixed methods and case study research.

The 15 participating farmers delivering grain to the Kwekwe GMB depot were chosen through simple random sampling. Simple random sampling gives each eligible participant an equal chance of being chosen and minimizes chances of selection bias. As Kothari (2004) puts it, simple random sampling enhances objectivity and fairness in selecting participants. Also, according to Saunders et al. (2019), a mixture of purposive and probability sampling would result in more representative and rich research findings.

Sampling in this manner was appropriate because the data collected helped address all research aims and objectives in an efficient manner.

3.5 Data Collection Procedure

Data was collected from GMB employees and smallholder farmers at the Kwekwe depot in a manner consistent with the research design used for the study through a combination of quantitative and qualitative techniques. Prior to data collection, the researchers acquired

permission from the appropriate authority at the Grain Marketing Board (GMB), while the subjects were made aware of the purpose of the study. All respondents granted permission to participate in the research.

Structured questionnaires and semi-structured interviews were used as the main tools for collecting the data. Structured questionnaires were distributed to the 30 respondents and included mostly five-point Likert scale questions with responses ranging from Strongly Disagree (1) to Strongly Agree (5). The purpose of the questionnaires was to collect quantitative data pertaining to the research objectives, which include the impact of the grain storage enabled by AI on post-harvest losses, efficiency, grain quality, and agricultural programs.

A Likert scale is used in the study since it allows the participants to state the degree of agreement with different statements and collect numerical data that can be subjected to further analysis. According to Boone and Boone (2012), the use of Likert scales helps to measure attitudes, perceptions, and opinions regarding technological innovations and organizational practices.

The surveys were conducted electronically using KoboCollect, which is a tool that provides data capturing in real time and guarantees its accuracy and validity due to the reduction of the number of errors. Using KoboCollect ensured efficient collection, management, and retrieval of data while minimizing the chances of obtaining incomplete surveys due to the internal validation checks. The tool improved the process of data capturing in terms of reliability and efficiency.

Semi-structured interviews were held with selected GMB managers, warehouse supervisors, and technical personnel who were purposely chosen due to their expertise in grain storage. Interviews helped to obtain qualitative data about opportunities and challenges associated with the implementation and use of AI-based grain storage systems.

Semi-structured interviews are especially beneficial when one seeks in-depth explanations and insights of complicated organizational and technological problems according to Creswell and Creswell (2023).

Data was collected concurrently for both questionnaire survey and interview study according to the convergent parallel mixed-method design. Concurrent data collection allowed the researcher to get complementary information from various sources which were then combined in the

process of analysis and interpretation of data to give an in-depth insight about the role of AI enabled grain storage in improving agricultural development programs at Kwekwe GMB.

3.6 Data analysis procedure

KoboCollect data was downloaded and cleaned and coded in Microsoft Excel before analysis using Statistical Package for Social Sciences (SPSS) Version 27. The quantitative data collected from the structured questionnaire survey was analyzed using descriptive and inferential statistical methods. Descriptive statistics, such as frequencies, percentage, means, and standard deviation were employed to summarize the demographic data and respondents' perceptions about AI-enabled grain storage systems. Mean scores were interpreted using five-point Likert scale.

The inferential statistics were used for hypothesis testing and determination of the relationships between AI-powered grain storage technology and various variables like post-harvest loss reduction, efficiency, grain quality management, and agricultural development outcomes. For instance, correlation analysis was used to find the magnitude and nature of the relationships between the variables, whereas the regression analysis was used to determine the influence of the independent variable on the dependent ones. The results of the analysis were illustrated using tables, charts, and graphs.

Qualitative data collected using semi-structured interviews was transcribed and subjected to thematic analysis. In particular, the researcher sought to identify recurrent themes, patterns, and concepts relating to the opportunities, challenges, effectiveness, and future of AI-powered grain storage systems. According to Braun and Clarke (2022), thematic analysis is a powerful method that allows researchers to structure qualitative data by identifying emerging themes.

Consistent with the thesis guidelines adopted by the study, the analyzed data were presented in two research papers, namely Chapters Four and Five. The former paper analyzed the operational aspects of AI-powered grain storage technology with focus on its effect on post-harvest loss reduction, operational efficiency, and grain quality management in Kwekwe GMB.

This manuscript covered Objectives One and Two of the study. The second manuscript considered the wider developmental impacts of AI-enabled grain storage systems, evaluating how these systems contribute to agricultural development programmes, food security, and smallholder farmers, and at the same time evaluating the opportunities and challenges with using

AI in Zimbabwe's grain storage systems. This manuscript covered Objectives Three and Four of the study.

The division of results into two manuscripts facilitated an in-depth evaluation of each of the themes and ensured that all the research objectives were considered. In addition, findings obtained from both quantitative and qualitative data were used during interpretation to increase validity by applying triangulation in method and gain a comprehensive understanding of the role of AI-enabled grain storage in promoting agricultural development programmes in Zimbabwe.

3.7 Research Ethics

In this research, ethical principles were followed throughout to ensure that participants were protected and that the study was credible. Before collecting any data, permission to undertake the research was obtained from the appropriate GMB Kwekwe depot authority. Participants were informed about the aims, objectives, and importance of the study before participating.

The participation of the respondents was fully voluntary, and prior to administration of questionnaires and interviews, all respondents provided their consent.

The participant confidentiality and anonymity was guaranteed because no names or other personal details of the participants were recorded on the questionnaire or interview forms. All the information gathered from respondents was for academic use only, and it did not get to unauthorized individuals. Data collected from KoboCollect was safely kept using password-protected devices and computer databases in order to avoid any loss or misuse of information.

The participants were made aware of the option to refuse to take part or withdraw from the study at any time without suffering any form of punishment. There was also guarantee that no harm in form of physical, psychological, social or financial damage would be done to participants in the course of the study. There was honesty and professionalism in the conduct of the research. Also, the results were reported in an objective manner without fabrication or falsification of data, thus adhering to the principles of research integrity and academic honesty as recommended by Creswell and Creswell (2023) and Saunders et al. (2019).

3.8 Summary

The chapter above outlined the methodological framework employed in the research. In this chapter, a description was made of the study area, research approach, sample size and selection,

data collection methods and analysis, and how all these were used to find out the impact of artificial intelligence-enabled grain storage on agricultural development programmes at Kwekwe GMB. Also covered in the chapter were the data collection and analysis methods using questionnaire, interview, KoboCollect, and SPSS, as well as the process involved in writing the two manuscripts outlined in Chapter Four and Five.

CHAPTER 4

DATA PRESENTATION INTERPRETATION AND ANALYSIS

4.0 Introduction

The current chapter includes analysis and discussion of the results generated through the survey conducted among respondents from GMB Kwekwe depot regarding the effects of AI in grain storage for agricultural development programs. Questionnaire was used for collecting data, which was then subjected to statistical analysis such as frequencies, percentages, tables, and charts. Qualitative data were categorized into themes in order to enrich the statistical results. The chapter first gives details about the demographic features of respondents and then highlights findings in relation to the objectives. These findings will be discussed in the context of the theoretical framework of diffusion of innovation theory and technology acceptance model.

4.1 Data Presentation Process

After data collection, all returned questionnaires were sorted and cleaned to guarantee completeness, accuracy, consistency, and relevancy of responses prior to analysis. Each of the 27 questionnaires was scrutinised for completeness, duplications and inconsistency, and all questionnaires turned out to be complete enough to be included in the study, hence a 100% usable response rate. Quantitative data were then coded and categorised based on the research objective. In this case, these include reduction of post-harvest losses, efficiency, contribution towards agricultural development programs and issues surrounding AI-enabled grain storage. Quantitative data analysis was done using descriptive statistics such as frequency, percentage, mean and standard deviation, while data obtained through qualitative open-ended questions was arranged thematically. Organising data according to the research objectives facilitated their analysis, presentation, and interpretation to answer research questions appropriately. Tables, graphs, and thematic analyses were utilised for presentation of the results in a meaningful way to facilitate comparison of responses, especially regarding the effect of AI-enabled grain storage on agricultural development programs in GMB Kwekwe Depot.

4.1.1 Data Cleaning and Preparation

Data cleaning and preparation were undertaken just after the completion of data collection to ensure data quality, accuracy, and reliability. Questionnaires were distributed to 27 respondents who were made up of GMB employees, farmers, managers, and other stakeholders of GMB Kwekwe Depot. In all, the researcher managed to obtain 100% responses from the 27 questionnaires, meaning there is enough data to make meaningful analysis and interpretation of the study findings. After distributing and collecting questionnaires from respondents, each questionnaire was then checked for accuracy, completeness, and consistencies. Missing entries, duplicates, contradictions, and recording mistakes in data that might have affected data integrity were identified and removed before coding. Each response in the Likert scale questionnaire was converted into numerical form whereas open-ended responses were categorized thematically based on predetermined categories. While there was partial response from some respondents in relation to the open-ended questions, their absence had no effect on data accuracy and completeness; therefore, analysis and interpretation were done accordingly based on responses received.

4.1.2 Data Screening and Cleaning

Data screening and cleaning were done immediately after data collection to guarantee the reliability, credibility, and validity of the data collected. In this regard, 27 questionnaires were issued to respondents at GMB Kwekwe Depot and 27 questionnaires were returned giving a response rate of 100%. The returned questionnaires were scrutinized for any inconsistencies, errors, inaccuracies, or contradictions before analysis. The researcher checked whether there were missing responses, duplications, errors of recording or contradictions among other possible factors that may compromise the validity of the results obtained. Minor inconsistencies identified during scrutiny were sorted out using verification against the answers given. Quantitative data were coded to form numerical values for ease of analysis. Qualitative data were analyzed to enable the extraction of themes from the open ended answers. It is noteworthy that although very few respondents failed to answer some open ended questions, the missing data were quite negligible and did not have a significant effect on the entire dataset. All questionnaires that were

returned were therefore usable for analysis. Data screening and cleaning were critical in ensuring that data analyzed for the purpose of answering research questions were reliable and valid.

4.1.3 Data Organisation and Coding

In the next stage after screening and cleaning, the data collected was organized and coded to allow for effective analysis and interpretation. Data that were collected quantitatively through closed-ended questions were coded using numbers, especially Likert scale questions in which Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree options were assigned number codes to allow for statistical analysis. Responses collected open-endedly were scrutinized and coded based on similarity in their meanings and content. Organization of data was influenced by the objectives of the study in that data related to each research question were categorized accordingly. Data on the first research objective were organized under post-harvest loss reduction, whereby grain spoilage, reasons for losses, and ways of minimizing losses were highlighted. Responses pertaining to the second objective were organized under operational efficiency, whereby questions about monitoring, automation, reduced labour force and enhanced decision making were answered. Information related to the third objective was organized under development impacts, whereby questions regarding food security, farmers' income and improved grain quality were examined.

4.1.4 Response Rate Analysis

The researcher administered thirty (30) questionnaires to selected participants who comprised employees, farmers, and managerial staff of GMB Kwekwe Depot. Out of the total number, twenty-seven (27) completed questionnaires were returned by the participants. These 27 returned questionnaires were found to be fit for analysis, resulting in a 90% response rate. This high response rate was viewed to be satisfactory since it surpassed the minimal required response rate for conducting research. In his study, Creswell (2018) observes that high response rates make research findings more representative and reliable due to minimisation of non-response bias. Saunders et al. (2019) also note that a high response rate (above 70%) can be considered satisfactory since such research generates credible and generalisable results. As a result, the obtained response rate of 90% was deemed excellent and made it possible to conduct an analysis

of perceptions of respondents regarding the effects of using AI in storing grains in agricultural development programmes within GMB Kwekwe Depot.

Table 4.1: Response Rate

Research Instrument	**Distributed**	**Returned**	**Response Rate (%)**
Questionnaire	30	27	90
Total	**30**	**27**	**90**

The findings revealed by Table 4.1 show that the study had a response rate of 90% since many respondents took part in the study. It can therefore be noted that the response rate raised the validity of the findings and made people have faith in the conclusions drawn from the study. There was very high participation because of the applicability of the topic to the respondents' working environment, as well as the researcher's effort in following up to ensure the validity of the collected data.

4.2 Demographics of Respondents

This subsection will discuss the demographics of the respondents that took part in the research. Demographics were thought to be significant since they could offer an understanding of the background of respondents and would help determine whether the respondents had the knowledge, experience, and exposure needed for credible responses about the influence of AI-based grain storage facilities on agriculture projects in GMB Kwekwe Depot. The demographic factors that were taken into consideration include gender, age, occupation, and experience.

4.2.1 Gender Profile

Gender profile of the respondents is discussed in Fig 4.1.

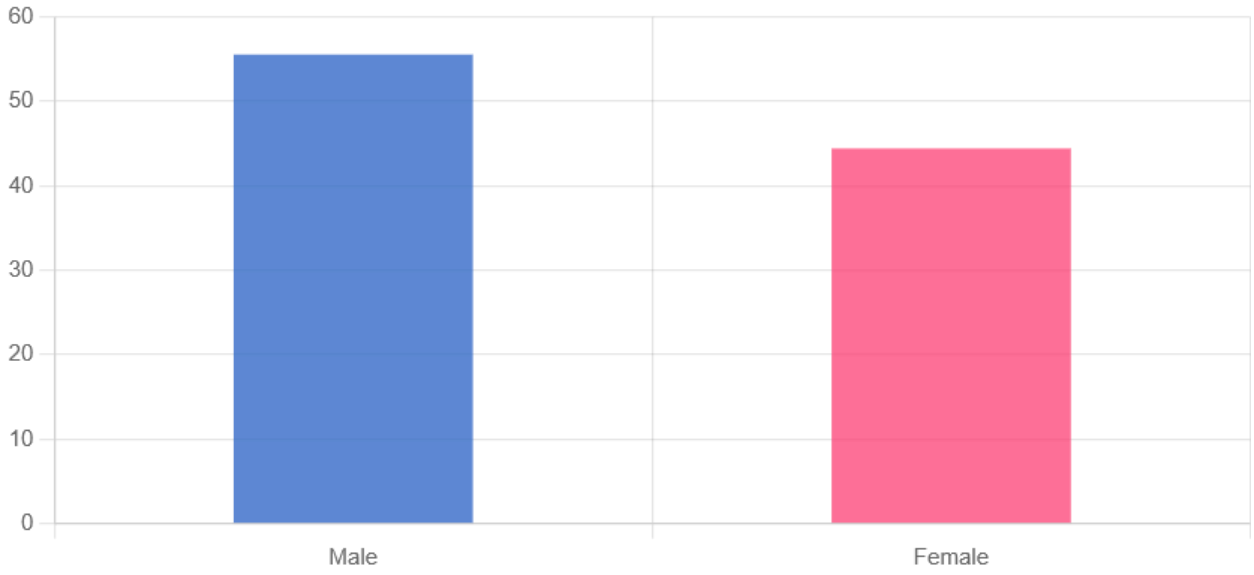


Table 4.2: Gender Distribution of Respondents

Gender	Frequency	Percentage (%)
Male	15	55.56
Female	12	44.44
Total	**27**	**100**

From Table 4.2 above, male participants were 55.56% (15) while females comprised 44.44% (12). The findings reveal a relatively balanced demographic in terms of gender since there is a slight majority of males in the survey. It means that both males and females participate in the storage of grains and other agricultural practices in GMB Kwekwe Depot. Consequently, they can offer different perceptions concerning the implementation and success of AI in the grain storage technology. Participation of both genders increases the validity of the findings considering that technological advancements in agriculture have started affecting both female and male stakeholders. Indeed, the findings corroborate those of FAO (2021) who found that in agricultural technology adoption, the two genders participate although the male gender plays more operational and technical roles than females. For instance, Oladele (2011) found that in agricultural technology programs, males have a slightly higher participation rate since they are

involved in production and management activities. However, a significant number of females in the current study demonstrates the increasing involvement of women in agricultural value chains and technology-based agricultural activities according to Hove et al. (2024).

4.2.2 Age Distribution

The age distribution of respondents is presented in Table 4.3.

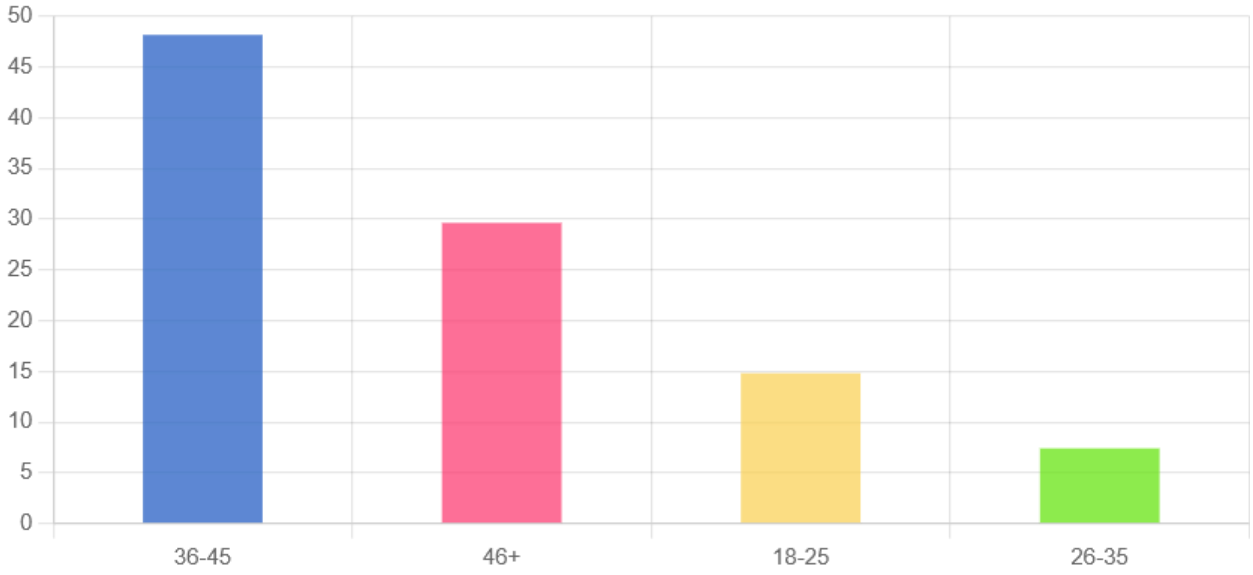
Table 4.3: Age Distribution of Respondents

Age Group (Years)	Frequency	Percentage (%)
18–25	**4**	**14.81**
26–35	**2**	**7.41**
36–45	**13**	**48.15**
46+	**8**	**29.63**
Total	**27**	**100**

Table 4.3 reveals that the highest percentage of the respondents, 48.15% (13), belonged to the age group of 36-45 years, followed by 29.63% (8) of respondents who fell into the age group of 46 years and older. Respondents belonging to the age group of 18-25 years accounted for 14.81% (4) of the total number of responses, while those falling into the age category of 26-35 years made up 7.41% (2). The high number of responses received from individuals belonging to the age groups of 36-45 and 46+ years implies that the majority of the participants had ample professional experience and practical insight into grain storage. Individuals belonging to such age categories are usually involved in decision making and management; hence, it makes sense to obtain information about AI-based grain storage system from such people. In the same way, Rogers (2003) notes that age is an important factor affecting technology adoption since individuals who have plenty of experience are well-placed to judge the usefulness of innovative products. Similarly, according to Dearing (2009), individuals with experience are key players when it comes to technology adoption in organizations. Venkatesh and Davis (2000) go further

to posit that perceived usefulness and ease of use of AI technologies. The below Fig 4.2 illustrates the above findings.

Fig 4.2 Age demographics of participants



4.2.3 Occupational Category

The occupational categories of respondents are presented in Fig 4.3 and Table 4.4

Fig 4.3 Occupational Category

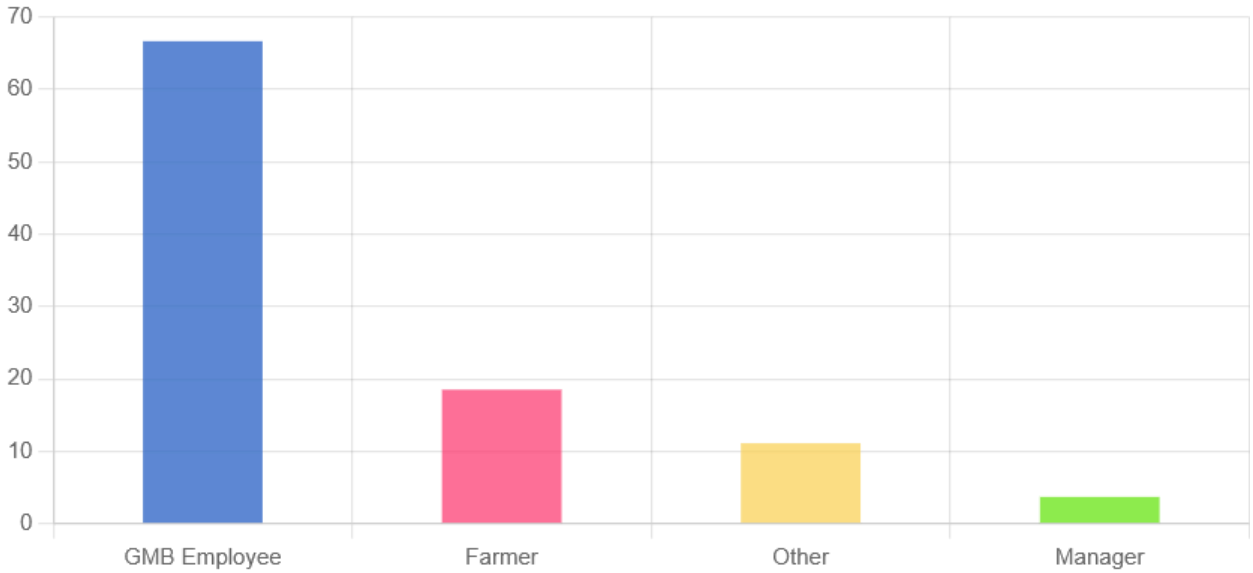


Table 4.4: Occupational Category of Respondents

Occupation	Frequency	Percentage (%)
GMB Employee	18	66.67
Farmer	5	18.52
Manager	1	3.70
Other	3	11.11
Total	**27**	**100**

From the data contained in Table 4.4, it can be seen that GMB employees made up the bulk of the respondents, representing 66.67% (18) of the total respondents. Farmers comprised 18.52% (5), while other respondents comprised 11.11% (3). The remaining 3.70% (1) represented managers. This was an expected pattern because GMB employees were expected to have direct experience dealing with grain storage facilities, and thus would have firsthand knowledge about the effectiveness of AI-driven grain storage systems. It was also reasonable to include farmers since they were among the major beneficiaries from improved grain storage methods by virtue of reduced losses and market accessibility. Having other respondents, including managers, also contributed to obtaining information from various angles. In this regard, the occupational distribution of the respondents helped provide valid information from those who had first-hand experience in grain storage and management.

4.2.4 Years of Experience

The years of experience of respondents were analysed using descriptive statistics and are presented in Table 4.5.

Table 4.5: Years of Experience of Respondents

Statistic	Value

Mean	12.11
Median	15.00
Mode	20.00
Standard Deviation	8.16

From Table 4.5, respondents had an average number of 12.11 years of experience in their respective work. The median was 15 years, while the mode was 20 years. Despite having a relatively large standard deviation value of 8.16 years, the findings of the survey reveal that most of the participants had considerable experience in grain handling, storage management, and farming operations. Based on the median and mode of the findings of this study, it is evident that most of the respondents were working in the industry for more than ten years, which means they had adequate practical experience of storing grains and using technological intervention in the processes. This means that the respondents' answers are more reliable, credible, and valid because they have witnessed developments in the grain storage process through time and can offer valuable suggestions about the efficiency of artificial intelligence-enabled storage techniques.

4.3 AI-Based Grain Storage and Reduction of Post-Harvest Losses

In this part of the report, the author will present the findings on the use of artificial intelligence-based grain storage to reduce post-harvest loss experienced at GMB Kwekwe Depot. Post-harvest loss is a common challenge in agriculture that occurs because of food spoilage, pest infestations, variations in moisture levels, among other things, during grain storage. Artificial intelligence technologies have been designed to solve this challenge using real-time monitoring, predictive analytics, and automation technologies. These findings will be classified under different themes according to whether respondents felt post-harvest loss was a major problem, how efficient artificial intelligence technology was in reducing grain spoilage, main causes of loss, and how to minimise loss.

4.3.1 Perceptions of Post-Harvest Losses at GMB

The participants were required to express their opinions on the statement that post-harvest losses were a major challenge at GMB Kwekwe depot. The findings are shown in Table 4.6 below.

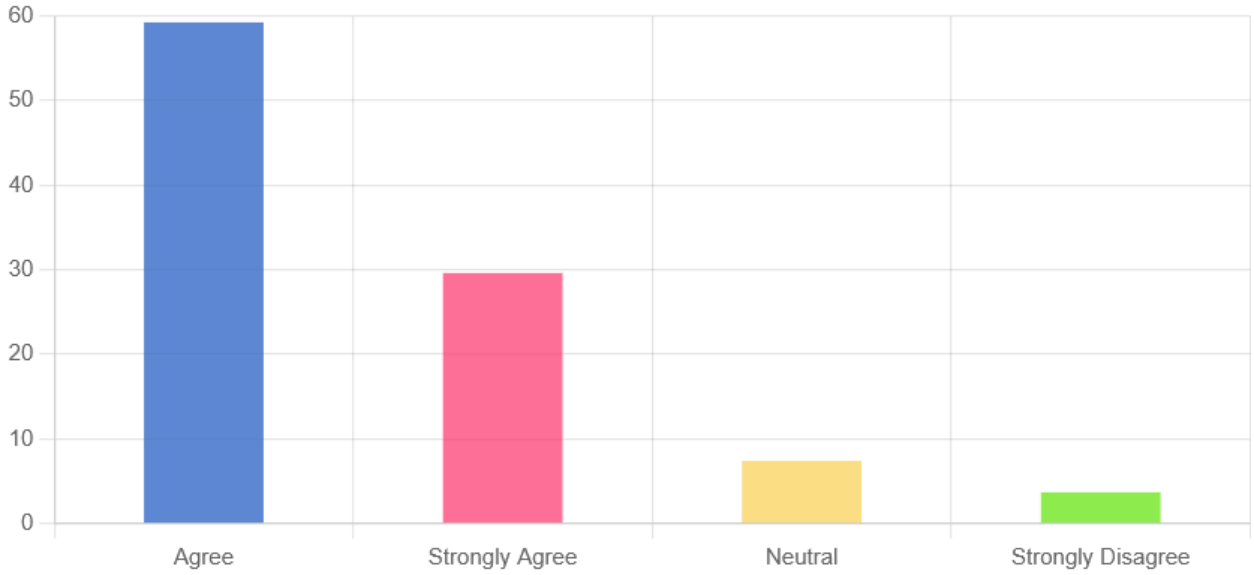
Table 4.6: Perceptions of Post-Harvest Losses at GMB

Response Category	Frequency	Percentage (%)
Strongly Agree	**8**	**29.63**
Agree	**16**	**59.26**
Neutral	**2**	**7.41**
Strongly Disagree	**1**	**3.70**
Total	**27**	**100**

These findings imply that post-harvest losses have been viewed as a very important problem by most respondents at GMB Kwekwe depot. More than three-quarters of respondents (88.89%) agreed (59.26%) or strongly agreed (29.63%) that post-harvest losses are an important problem, while only 3.70% of respondents strongly disagreed and 7.41% did not express any view.

The above findings agree with the research done by Affognon et al. (2015), where post-harvest losses are regarded as the main challenges for agricultural productivity and food security in Sub-Saharan Africa. Likewise, according to Gustavsson et al. (2011), there are notable amounts of post-harvest losses that happen in Sub-Saharan Africa after harvesting due to poor storage conditions and pest attacks. Hodges et al. (2014) reported that post-harvest losses lower the levels of food availability, income for farmers, and efficiency of the agricultural supply chains. This study has therefore found that post-harvest losses still present challenges in the Zimbabwean grain storage industry that require technological solutions. This is further illustrated with the bolw fig 4.4

Figure 4.4 Perceptions of post-harvest losses



4.3.2 Effectiveness of Artificial Intelligence in Reducing Grain Spoilage

Table 4.7 Effectiveness of AI in Reducing Grain losses

Response Category	Frequency	Percentage (%)
Strongly Agree	6	22.22
Agree	15	55.56
Neutral	3	11.11
Disagree	2	7.41
Strongly Disagree	1	3.70
Total	**27**	**100**

It is evident from Table 4.7 that 77.78% of the respondents strongly agree that artificial intelligence technology in grain storage ensures reduced grain spoilage. 11.11% disagreed or

strongly disagreed, while 11.11% were neutral. This indicates that the respondents have a lot of faith in the capabilities of AI technologies to ensure minimum grain spoilage during storage. The positive perception on the effectiveness of AI technologies stems from the capability of intelligent systems to detect in real-time changes in conditions like the temperature, humidity and the moisture content of grain. This ensures that potential risks are identified and mitigated before causing any losses. This is consistent with the findings of Chen et al. (2019), which indicate that monitoring through artificial intelligence ensures reduced spoilage as it allows for predictive analytics and automated environmental controls. Also, according to Zhao & Xue (2021), sensor-based grain management ensures improved storage performance since there is real-time detection and mitigation of risks. Moreover, as suggested by Kitinoja & Kader (2015), advanced storage technologies are crucial in ensuring the quality of grain during storage.

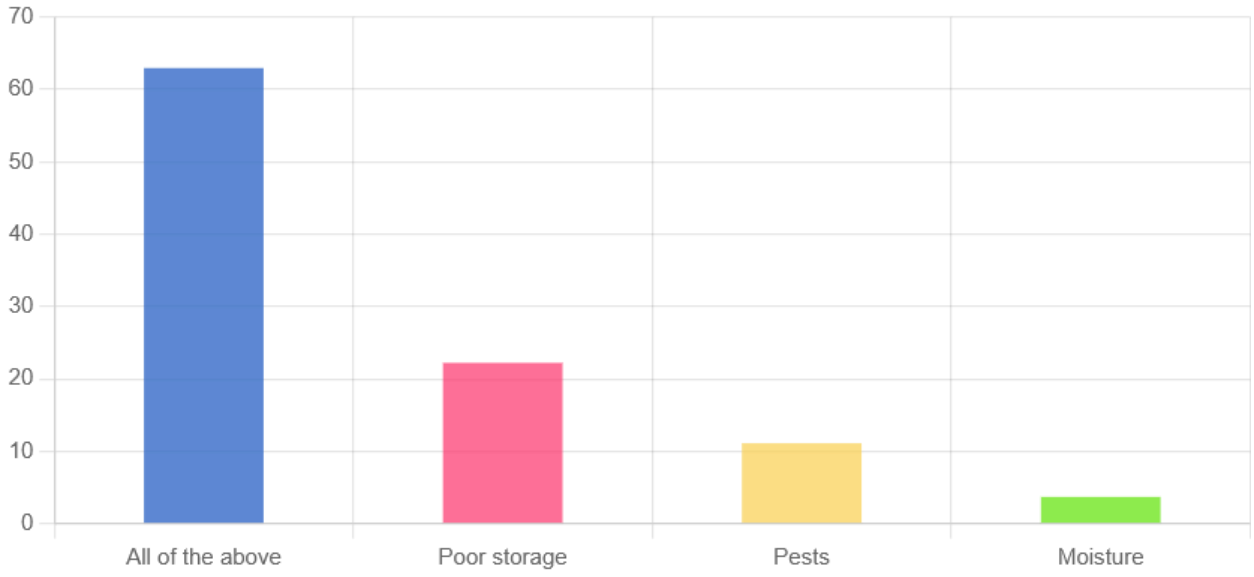
4.3.3 Major Causes of Grain Losses

Respondents were asked to identify the major causes of grain losses during storage. The results are presented in Table 4.8.

Table 4.8: Major Causes of Grain Losses

CAUSE OF GRAIN LOSS	FREQUENCY	PERCENTAGE (%)
ALL OF THE ABOVE	17	62.96
POOR STORAGE	6	22.22
PESTS	3	11.11
MOISTURE	1	3.70
TOTAL	**27**	**100**

Fig 4.5 Major causes of Grain losses



According to the results, it can be observed that 62.96% of the respondents opted for "All of the above" indicating that the losses incurred on the grains emanated from multiple causes rather than a single cause. 22.22% of the respondents indicated that the loss occurred due to poor storage while another 11.11% of the respondents pointed out that pest attack led to losses. Additionally, 3.70% of the respondents cited poor moisture control as the reason behind the losses.

The findings above clearly indicate the complex nature of the post-harvest losses. Moisture control is very important as the excess moisture in the grains provides a conducive environment for the growth of the fungi which leads to the loss of quality. Proper pest control is also important because the pests would consume huge amounts of the grains especially in the absence of protection against the pests. The storage conditions such as temperature and storage structure must also be considered when storing the grains. The findings are similar to those established by Gustavsson et al. (2011) whereby storage losses occurred due to poor storage structures, pest infestation, and moisture management.

4.3.4 Strategies for Minimising Grain Losses

Based on the analysis, the results revealed that fumigation was one of the frequently mentioned strategies that can be used to minimize grain losses with ten mentions, followed by moisture control with seven mentions and proper storage facilities with six mentions. Monitoring systems and pest control received five and four mentions correspondingly. Therefore, the analysis reveals

that respondents see the benefits of using both preventive and corrective measures as an important part of effective grain storage management. Specifically, the prevalence of fumigation and pest control techniques can be attributed to the understanding of the risk of infestation and biological deterioration of stored grain. The relevance of moisture control is linked to the need to keep the moisture level within the acceptable standards to prevent deterioration. The use of proper storage facilities is related to the provision of safe environment protection.

Of particular importance is the mention of monitoring systems which indicates awareness of how effective technologies can be used to minimize losses. Indeed, intelligent monitoring systems can continuously monitor grain storage and provide timely warning alerts in case of abnormal temperature, humidity and infestation levels. Hence, the analysis shows that loss reduction can be facilitated by using intelligent monitoring systems.

4.3.5 Discussion of Results Regarding Post-Harvest Loss Reduction

Overall, the findings regarding post-harvest loss reduction suggest that AI-powered grain storage technology has immense potential in terms of addressing one of the biggest problems in agricultural development programs. The vast majority of respondents believed that post-harvest losses were still a big problem and felt confident about the potential of AI technologies in reducing the spoilage of grains by means of effective monitoring and management. Additionally, the respondents understood that such losses resulted from numerous interdependent factors such as moisture, pests, as well as improper storage, all of which could be managed with intelligent storage technology.

In particular, the above-stated findings confirm the conceptual framework that was utilized in the current study. According to this conceptual framework, the introduction of AI-powered grain storage in agricultural development programs is beneficial because of the decrease in post-harvest losses, which increases the efficiency of storage and, consequently, leads to more efficient utilization of the harvested grains. At the same time, the findings are consistent with Rogers' (2003) Diffusion of Innovation Theory. The high degree of consensus concerning the effectiveness of AI indicates that the interviewees have an understanding of some of the advantages of utilizing such technology in grain storage. Moreover, the research findings are congruent with previous studies by Affognon et al. (2015), Chen et al. (2019), Zhao and Xue (2021), Gustavsson et al. (2011) and Kitinoja and Kader (2015), which found out that current

storage practices greatly mitigate waste through improved grain preservation and security. All things considered, AI-assisted grain storage can be considered as a viable approach to combating wastage in Zimbabwe.

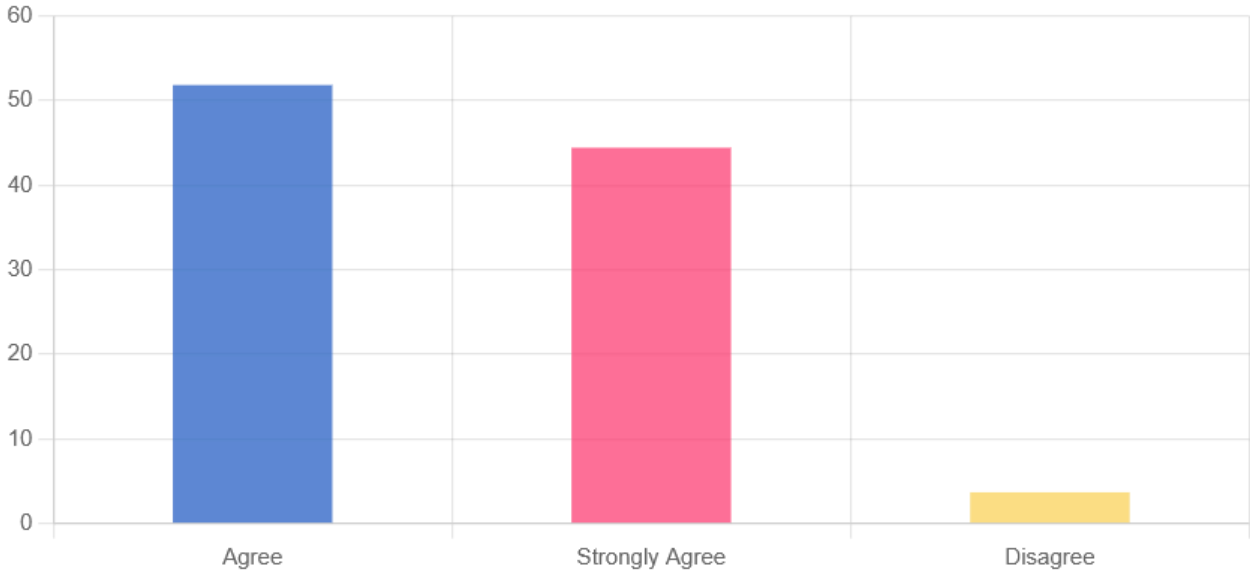
4.4 AI-Assisted Grain Storage and Efficiency

The following discussion relates to the second objective of this study that aimed to assess the impact of AI-assisted grain storage on efficiency in GMB Kwekwe Depot operations. As highlighted by previous literature, operational efficiency is an important driver of organisational performance since it determines such aspects as efficiency, productivity, information accessibility and effective decision making. AI-assisted storage solutions enable organisations to automate routine activities, enhance their surveillance mechanisms, increase information accessibility and make better-informed decisions. Thus, the following analysis will focus on the findings concerning the areas of monitoring efficiency, automation, decreased workloads and effective decision making.

4.4.1 AI and Monitoring Efficiency

Respondents were asked to indicate whether AI-enabled grain storage improves monitoring processes. The results are presented in Fig 4.6.

Fig 4.6 AI and Monitoring Efficiency



The findings show that 96.29% of participants agreed or strongly agreed that the use of AI technologies facilitates more efficient monitoring and supervision in grain storage activities, whereas 3.70% did not agree. It is evident that participants have great faith in the capacity of AI technologies to facilitate better monitoring and supervision processes of grain storage operations. Respondents viewed the use of AI technologies as useful in providing timely information concerning grain storage operations.

The findings show that through automation provided by artificial intelligence technologies, managers will be able to carry out continuous monitoring and surveillance of various storage parameters including temperature, humidity, and the condition of stored grains. In other words, managers will be able to detect potential problems and act accordingly without waiting until the situation escalates to significant levels. As suggested by Chen et al. (2019), intelligent monitoring technologies make grain storage operations easier to monitor. According to Anukiruthika and Jayas (2025), AI-powered monitoring technologies help in making grain storage operations more efficient by carrying out continuous monitoring. Hence, automation makes grain storage operations efficient.

4.4.2 Automation and Work Reduction

Participants were asked whether automation makes work easier or not. The findings are shown in Table 4.11.

Table 4.11: Automation and Work Reduction

Response Category	**Frequency**	**Percentage (%)**
Strongly Agree	8	29.63
Agree	15	55.56
Neutral	2	7.41
Disagree	2	7.41
Total	**27**	**100**

The findings show that 85.19% of the respondents were in agreement that automation decreases the amount of work done, 7.41% disagreed, and 7.41% were neutral. This implies that most of the respondents view automation as an effective approach in decreasing the amount of manual labour required in operational procedures in grain storage companies. Automation is viewed positively due to the fact that automation performs repetitive monitoring, data collection, and reporting functions with minimum intervention from humans. Automation helps in reducing the frequency of manual inspections required, hence making the process of performing these functions more efficient. The respondents stated that automation makes the process more efficient since they require little labour and complete the process quickly. This finding aligns with that presented by Leistritz & Bangsund (2018) where they noted that automation helps in increasing productivity through reduction in labour intensity. Likewise, according to Chen et al. (2019), automation improves efficiency and effectiveness in grain management process.

4.4.3 AI and Decision-Making Effectiveness

To evaluate the contribution of AI technologies to managerial effectiveness, respondents were asked whether AI improves decision-making. The findings are presented in Table 4.12.

Table 4.12: AI and Decision-Making Effectiveness

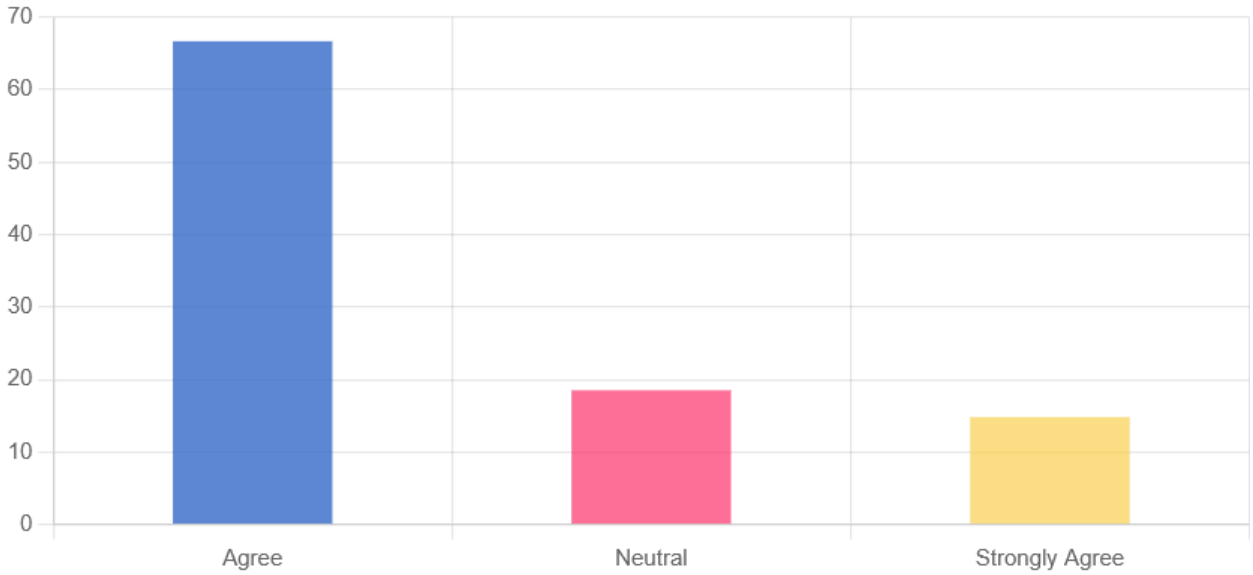
Response Category	**Frequency**	**Percentage (%)**
Strongly Agree	4	14.81
Agree	18	66.67
Neutral	5	18.52
Total	**27**	**100**

As seen in Table 4.12, 81.48% of the respondents agree with the opinion that AI helps to make better decisions in terms of storage. The remaining percentage of people, 18.52%, stayed neutral. No one disagrees with the opinion. Hence, the importance of having proper information from AI technologies can be clearly seen. Managers need such information in order to take reasonable decisions about operations and strategy of grain storage facilities. Having access to necessary

information provided by AI systems can help managers take better decisions on storage management. Such systems give managers detailed information concerning current situations in storages and help managers make better decisions on managing grain storage facilities. According to Anukiruthika & Jayas (2025), such technological advances as artificial intelligence have a positive impact on making organisational decisions by processing huge amounts of data related to operations. Moreover, such an impact was found out by Chen et al. (2019) as well in the context of agricultural storage. Hence, using AI for storage purposes helps to make more efficient managerial decisions.

4.4.4 Perceived Efficiency Improvements

Respondents were asked to explain what benefits AI brings to grain storage operations in relation to efficiency. The analysis of their answers is provided in fig 4.7 below;



Theme	Frequency
Time Savings	10
Labour Reduction	8
Inventory Management	4
Reduced Spoilage	3

Cost Savings	3
Data Accessibility	3

As can be seen from the thematic analysis results, saving time is one of the key advantages identified in terms of efficiency, having been cited by ten respondents. The issue of labour reduction was named by eight respondents, while improved inventory management was cited by four. Reduced waste, saving costs and greater data accessibility were also among the top three responses mentioned, with each of those factors being noted by three people participating in the research. This allows us to conclude that efficiency is seen as a multilevel phenomenon including productivity gains, resource optimisation and better information management.

The significance of such aspects as saving time and reducing labour are linked to the automation possibilities offered by modern AI technologies. The respondents stated that the use of advanced solutions made some activities faster and required less effort from employees. In the case of inventory management, it refers to increased stock management capacity and more effective management of grain movement, while data accessibility means having access to real-time information about the operations. Saving costs and reducing waste were seen as secondary benefits achieved through better monitoring and process effectiveness. Findings regarding operational efficiency show that there are significant impacts of artificial intelligence technology towards improving the performance of an organisation through effective monitoring, automation, and decision-making processes. The majority of the participants confirmed that AI has greatly facilitated efficient monitoring, reduced the manual effort and assisted in better decision-making. From the qualitative analysis, it was also found out that participants associated the adoption of AI technology with saving time, labour efficiency, effective management of inventory, reduction of spoilage, reduction of cost, and accessibility of information.

The results obtained from the research have been validated in the Technology Acceptance Model (TAM) proposed by Davis (1989). This theory states that the use of technology depends upon perceived usefulness and ease of use of technology. Positive perceptions held by respondents

regarding the use of AI technology show that respondents consider the usefulness of this technology for making the operations more effective. These results also align with the Diffusion of Innovation Theory presented by Rogers (2003). In accordance with the theory, innovations are adopted easily if users find any relative advantage in adopting new technology.

This research finding is consistent with findings obtained in previous studies. According to Leistritz and Bangsund (2018), the use of automation technology increases efficiency in operations because of reduced labor costs and increased consistency. Similarly, Chen et al. (2019) identified the fact that the use of intelligent technology through monitoring and prediction in grain storage systems improves efficiency. This was attributed to effective process control and decision-making based on available information. Besides, Anukiruthika and Jayas (2025) noted that intelligent storage technology increases efficiency due to better optimization of resources, inventory management, and organizational responsiveness. Hence, the results obtained in this study suggest that intelligent grain storage systems are efficient and an innovative technology in agricultural storage at GMB Kwekwe Depot.

4.5 Contribution of AI Enabled Grain Storage to Agricultural Development Programmes

In this section, the results obtained from research on issues related to the third research objective of the study will be presented. Agriculture development not only involves improvements made in grain storage but includes many other factors such as improvement in food security, income generation, grain quality management among others. AI enabled grain storage systems enhance all these benefits through reduction in post-harvest losses, storage management and making informed decisions. The results have been organized into themes that cover food security, farmer income, grain quality management and overall contribution of AI systems in agriculture development.

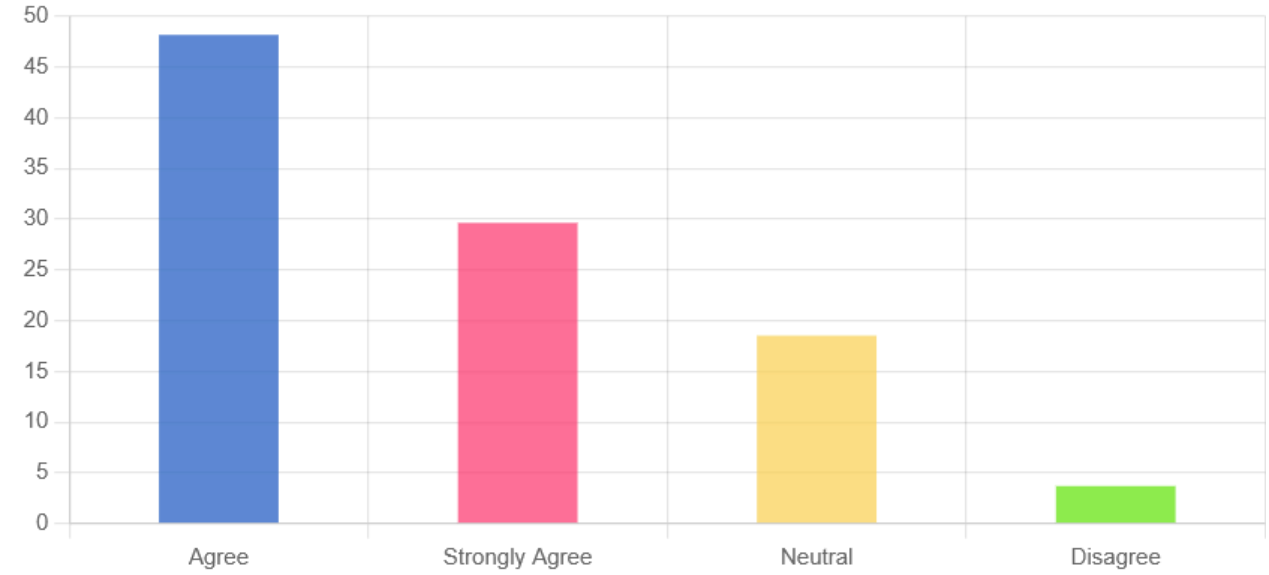
4.5.1 Contribution to Food Security

The respondents were required to state whether AI enabled grain storage enhanced food security. These results have been captured in Table 4.14.

Table 4.14: Contribution of AI to Food Security

Response Category	Frequency	Percentage (%)

Strongly Agree	8	29.63
Agree	13	48.15
Neutral	5	18.52
Disagree	1	3.70
Total	**27**	**100**



From the results, it is evident that 77.78% of the sample population agreed that artificial intelligence in grain storage contributes to food security. In addition, 18.52% of the respondents had neutral views concerning whether artificial intelligence contributes to food security in Zimbabwe's agriculture. Furthermore, only 3.70% of the respondents disagreed with the above statement. It can be concluded from the findings that the respondents have high confidence in the contribution of artificial intelligence technology in the improvement of food security by enhancing grain storage management.

According to the results, AI positively impacts food security because it helps in the reduction of losses after harvesting. The technology ensures grain storage management and helps to keep the quality and supply of grains stable during the period of storing. Through this process, AI

technology plays an instrumental role in increasing grain availability and distribution. Thus, the results align with the argument made by the Food and Agricultural Organization (FAO, 2021). According to FAO (2021), decreasing the rate of losses after harvest is one of the ways of enhancing food security. Also, the World Bank (2018) affirms that advanced technology improves food system resilience by ensuring minimal losses and availability.

4.6 Challenges and Opportunities for Adoption of AI-Enabled Grain Storage

This section discusses the findings regarding the fourth research objective, which focused on examining the challenges and opportunities for adoption of the AI-enabled grain storage system at GMB Kwekwe Depot. Despite the many benefits provided by AI technologies in terms of reducing post-harvest losses and enhancing efficiency, there are a number of factors that influence the adoption of such systems in organisations. It is therefore important to understand these challenges and opportunities as a way of developing strategies for ensuring adoption.

4.6.1 Challenges Facing AI Adoption

The survey respondents were requested to indicate the major challenges facing the adoption and use of AI-enabled grain storage systems. These findings are summarised in Table 4.18.

Table 4.18: Challenges Facing AI Adoption

Challenge	Frequency	Percentage (%)
Lack of Skills	15	55.56
High Cost	10	37.04
Poor Infrastructure	6	22.22
Resistance to Change	4	14.81

From the study results, it can be noted that the lack of skills emerged as the biggest obstacle to the adoption of AI technology, which was indicated by 55.56% of the respondents. Implementation costs were highlighted by 37.04% of the respondents while poor infrastructure and resistance to change emerged as challenges indicated by 22.22% and 14.81% of the

respondents respectively. The findings clearly show that human capacity weaknesses, cost issues and infrastructural weaknesses continue to represent serious barriers in the implementation of AI enabled storage technologies.

Skills shortage as the biggest obstacle is an indication that a number of stakeholders do not have sufficient technical capacity to use and maintain the technologies. Hove et al. (2024) argue that insufficient technical capacity continues to be one of the biggest barriers to the adoption of agricultural technologies among developing nations owing to the difficulties experienced by the users to utilize digital technologies. Similarly, Oladele (2011) notes that lack of access to skills and technological knowledge makes the process of adoption difficult for agricultural stakeholders.

4.7 Discussion of Findings

This section contains an integrated discussion of the findings of the study. It differs from the previous sections in the sense that it combines the various findings of the study as a whole, giving a broader interpretation to the findings within the context of AI in grain storage at GMB Kwekwe Depot. The discussion in this section takes into account the conceptual framework of the study which is the Diffusion of Innovation Theory and the Technology Acceptance Model (TAM). The purpose is to establish how the various dimensions discussed in the earlier parts of this study make a difference in agricultural development.

4.7.1 Link Between AI Technologies and Reduction of Post-Harvest Losses

The findings of the current study point to the fact that there is a link between AI-enabled grain storage and post-harvest losses. According to the respondents, one of the biggest challenges facing grain storage is post-harvest losses while at the same time the same respondents were confident that AI technologies would help reduce the amount of grains that could be lost through spoilage. The main causes of grain losses identified include moisture variation, pests, among others, while fumigation and moisture regulation are important

The connection between AI and decreased post-harvest losses has provided robust backing to the study's conceptual framework where it was proposed that advanced technologies enhance grain preservation by ensuring real-time storage condition monitoring and automating control systems. In this way, interventions become possible due to early warnings about deteriorations which are

aimed at preventing grain losses. Consequently, decreased grain losses have contributed to grain availability and food security. Hence, the main hypothesis behind the conceptual framework has been proven; that technology innovation is a factor that triggers agricultural productivity and sustainability.

The results obtained can also be aligned with Rogers' (2003) theory on Diffusion of Innovations according to which innovations should provide a relative advantage over existing technologies and practices. The respondents perceived the benefits of AI-enabled systems in terms of increased grain longevity, better monitoring and control. It means that there is an opportunity for successful diffusion of the discussed innovation as people find the new technology advantageous to their operations and jobs. At the same time, the Technology Acceptance Model introduced by Davis (1989) states that technologies are accepted when people see that they are useful for them and allow them to improve work performance.

Indeed, these findings align well with earlier empirical studies. For instance, Affognon et al. (2015) stated that there is a need for improvements in storage technologies for minimising losses during post-harvest stages and improving food security in developing countries. Similar conclusions were drawn by Gustavsson et al. (2011), who asserted that poor storage systems account for the major part of food losses across the world and emphasised the role of innovative solutions in overcoming the problem. Moreover, Chen et al. (2019), Zhao and Xue (2021), and Kitinoja and Kader (2015) confirmed the ability of intelligent storage technologies to minimise losses owing to constant monitoring and prediction capabilities. Hence, this empirical research supports previous studies in terms of demonstrating that artificial intelligence enables efficient storage technologies that could serve as a solution to the challenge of losses in agriculture.

4.7.2 Relationship Between AI and Operational Efficiency

Furthermore, the findings indicate a significant positive relationship between AI and operational efficiency. Participants generally believed that artificial intelligence increases monitoring efficiency, saves employees' time and effort, and allows for making more accurate decisions. The observed changes in terms of operational efficiencies can be related closely to Technology Acceptance Model (TAM). Davis (1989) points out that individuals tend to accept technologies, which can help to increase their productivity and make their operations easier. Considering positive perceptions, which have been obtained during this research, it is safe to say that the

interviewed individuals see AI-based grain storage as a useful and beneficial technology for improving their daily operations. In turn, according to Venkatesh & Davis (2000), the usefulness of technologies affects behaviour of people positively. Thus, observed benefits are likely to foster continued use of artificial intelligence systems in grain storage facilities.

From the point of view of the Diffusion of Innovations Theory, the discussed changes in terms of operations can be seen as important determinants of technological innovation. In particular, Rogers (2003) notes that relative advantage, compatibility and observability are among the factors determining diffusion of innovations. Taking into consideration benefits provided by AI, which have been noted by the respondents, it should be concluded that these benefits were observable to stakeholders.

The results also corroborate the results of the previous work conducted by Leistritz and Bangsund (2018), which found that the use of automation technologies increases efficiency due to less need for labour and greater efficiency in processing. In addition, Chen et al. (2019) proved that AI technologies increase efficiency through the collection of real-time information and the use of analytics. Also, Anukiruthika and Jayas (2025) concluded that AI grain storage systems increase efficiency and optimise resource allocation. Overall, the mentioned research works and the current results indicate that AI technologies in grain storage systems are crucial for improving efficiency and organisational effectiveness.

4.7.3 Relationship Between AI and Agricultural Development Outcomes

It was also established that there exists a strong relationship between the adoption of AI technology in agricultural storage and agricultural development. Respondents agreed that using AI in agriculture contributes to increasing the efficiency of food storage and improving grain quality, which helps increase income. Moreover, enhanced monitoring, operational efficiency, increased capacity, forecasting capabilities, and quality management were identified as some of the important agricultural development outcomes of using AI technologies.

The results clearly indicate that the theoretical framework of the study is justified since it posited that there would be increased agricultural development due to efficient grain storage facilitated by artificial intelligence. Firstly, grain storage helps reduce post-harvest losses, increasing the amount of grain available for consumption and sales and thus improving availability, hence

contributing to food security of the country. Additionally, grain storage increases marketability due to improved quality and hence leads to greater economic gains. In effect, grain storage facilitates economic and food security development in agriculture.

The results of this study provide solid evidence in favor of the theoretical framework underlying the research which suggested that AI-enabled grain storage would contribute to agricultural development through increased efficiency, lower losses, better quality management and food security. First of all, the decrease in post-harvest losses will result in an increase in the volume of grains that can be consumed and sold, hence making the process of achieving food security in the country easier. On the other hand, improved quality conservation means increased competitive ability and profitability.

The link between the adoption of AI and agricultural development may also be understood in line with Diffusion of Innovations theory. According to Rogers (2003), innovations bring about social and economic development when adopted and integrated into organisational systems. The positive developmental aspects revealed in this study show that AI technologies have the potential to transform agricultural value chains by promoting efficiency and better resource management. Again, according to the technology acceptance model, the likelihood of adopting and using a certain technology is higher where the innovation generates positive benefits to users. The ability of AI technologies to promote food security and income generation hence brings a positive attitude towards adoption and use.

Findings of this study align with several other studies carried out by FAO (2021), who argues that improvements in storage management form an important part of agricultural development and food security promotion. In the same vein, World Bank (2018) observes that technological innovations enhance agricultural production, boost agricultural value chains, and promote rural development. Mhlanga (2014) and Nhamo (2019) equally assert that technological innovations enhance agricultural competitiveness and support economic development. Finally, Bongi and Chikozho (2020) observe that improvements in agricultural storage practices enhance efficiency in agricultural.

These results are similar to what other studies like FAO (2021) argue about the necessity of effective storage management in enhancing sustainable agricultural development and food

security. Moreover, according to World Bank (2018), innovative technology plays an important role in enhancing agricultural productivity and contributes to value chain improvement and rural development. Mhlanga (2014) and Nhamo (2019) also emphasize that technological innovations can help make agriculture more competitive and enhance economic transformation in developing countries. In addition, Bongi and Chikozho (2020) conclude that technologically advanced storage systems help improve quality management of agricultural markets. Thus, the findings of this study contribute further to the existing literature on the use of AI in agricultural development and sustainability.

4.7.4 Implications for GMB and Zimbabwe's Agricultural Modernization

First of all, the results of this study suggest that the implementation of AI technology in grain management can have an immense impact on the way GMB manages its operations. In addition, the results of the current research imply that technological innovation plays an important role in agricultural modernization in Zimbabwe. Indeed, the evidence presented here shows that grain storage technology is able to enhance grain management. In regard to GMB, the findings show the need for enhancing training of the staff members, enhancing technical systems, and investing in capacity development to maximize the advantages of using AI-enabled storage technologies. Respondents agreed that workshops and training programs can enhance the efficiency of technology usage. As per Davis (1989), adoption of technology is easier if the person knows about how to use the technology successfully. Likewise, according to Rogers (2003), communication, training, and knowledge help the adoption of innovation by organizations. The need for capacity development was emphasized again by Hove et al. (2024) who argued that capacity development is vital for digital transformation of organizations. Thus, human resource development is necessary for future expansion of technologies. The second recommendation from this study is related to infrastructural development in agricultural organizations. In this regard, respondents suggested the need for increasing AI enabled silos, efficient loading/unloading systems and technological support systems.

4.8 Chapter Summary

This chapter has therefore reviewed, analyzed and discussed the results that have been generated from the 27 participants in the study on AI technology in grain storage as a contributor to the agricultural development initiatives at the GMB Kwekwe Depot. Finally, the results related to the fourth objective indicated that despite challenges associated with the adoption of AI technology, which include lack of skills, high cost of implementation, poor infrastructural facilities, and reluctance to adopt the new technology, there is indeed potential for AI adoption, as it offers benefits like increased monitoring, improved efficiency, reduction in losses, and better profits. It is advised that staff training, conducting workshops, development of infrastructural facilities, extension of AI storage facilities, and provision of technical assistance should be done to improve AI adoption in grain storage.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

In this chapter, the summary, conclusions and recommendations of the research on the effect of AI in grain storage on agricultural development programmes at GMB Kwekwe Depot is outlined. This chapter summarises the key findings of the study concerning the research objectives and research questions, draws the conclusion based on the empirical findings, which were obtained through the process of carrying out the research and recommends policies that could be followed by management and other stakeholders. Furthermore, it shows how the research adds to the current body of knowledge and future areas of study. The conclusions are drawn from the findings made in Chapter Four in light of the theory and conceptual framework used in the study.

5.1 Summary of the Study

The purpose of the research was to analyse the effect of AI-enhanced grain storage technologies on agricultural development initiatives in GMB Kwekwe Depot. The study was based on several key factors that include the presence of post-harvest grain losses, inefficiencies of traditional grain storage systems, and the need for innovations that could help enhance agricultural performance and food security in Zimbabwe. While the application of AI technologies in

agricultural production processes is common in other countries, there has been a lack of data on the role played by AI in grain storage management and agricultural development in grain storage organizations in Zimbabwe.

Four objectives were set out as the main research questions and included exploring the effect of AI-enhanced grain storage on reduction of post-harvest grain losses, exploring the effect of the use of the same on efficiency in grain storage, exploring the impact of the technology on agricultural development, and identifying the challenges and opportunities of adopting such technologies. The study was grounded on Rogers' Diffusion of Innovation Theory and the Technology Acceptance Model, which gave theoretical explanations about technology adoption behavior and acceptance. A quantitative research method was used, based on the positivist paradigm. The data were obtained from structured questionnaires distributed to GMB Kwekwe Depot staff members, farmers, and managers. Altogether, twenty-seven questionnaires were distributed, with all being returned, achieving a 100% response rate. Data were analyzed quantitatively using descriptive statistics and thematic analysis, allowing for qualitative analysis of the data collected.

It was discovered that most of the respondents considered post-harvest losses as one of the greatest challenges faced during grain storage. In addition, the use of AI in grain storage technology allows for better grain preservation by improving monitoring, moisture control, pest control, and early detection of any issues related to grain storage. The AI system is also noted to greatly increase efficiency through accurate monitoring, reduced human effort, improved decision making, and efficient inventory systems. In addition to this, the study found out that the use of AI technology in grain storage contributes positively towards agricultural development in terms of improved food security, grain quality, efficiency in storage and economic opportunities. In addition to this, the findings from the study showed that the benefits of using AI technology in agriculture are immense but limited by a lack of skills, costs, poor infrastructure and opposition to change. As a result, more training, infrastructure, AI technology-based storage facilities and technical support should be encouraged.

5.2 Conclusions of the Study

5.2.1 Conclusions on the Reduction of Post-Harvest Losses

Based on the study results, it can be concluded that the use of AI technology in grain storage plays an important role in reducing post-harvest losses in the GMB Kwekwe Depot. From the results of the study, grain losses remain a significant issue during storage because of factors such as moisture levels, presence of pests and poor storage management. However, through AI technology, it is possible to detect these issues early enough.

Therefore, this research concludes that AI solutions are viable ways of mitigating post-harvest losses through environmental monitoring, prediction and automation of processes to improve grain conservation, as well as reduce both quantitative and qualitative losses. As a result, intelligent grain storage increases food availability, improves storage efficiency, and overall improves performance in grain storage operations. This is corroborated by the findings presented in the studies by Affognon et al. (2015); Gustavsson et al. (2011); Chen et al. (2019) and Zhao and Xue (2021). These authors have found that intelligent storage technology increases efficiency by reducing losses.

5.2.2 Conclusion on Operational Efficiency

Based on the findings of this study, it can be concluded that grain storage using AI technology at GMB Kwekwe Depot is very effective in enhancing operational efficiency. It was noted that the use of AI solutions in grain storage improves monitoring practices, automation, and decision-making processes. This resulted in better time management, less need for manpower and improved inventory management. In addition, the research finds that intelligent storage systems create a conducive environment for improved resource utilisation and overall efficiency. This is evident from the views shared by the respondents on the usefulness of AI storage systems in streamlining operations. Thus, the conclusions drawn above show that the use of AI-based grain storage is not only an innovative technology but also a managerial strategy that can enhance organisational performance. It is in line with research by Leistritz and Bangsund (2018); Chen et al. (2019) and Anukiruthika and Jayas (2025), who found that intelligent agricultural technology makes a significant contribution to efficiency improvements and process optimisation.

5.2.3 Conclusions on Agriculture Development Outcomes

From this research, it can be concluded that the implementation of intelligent grain storage contributes positively to overall agricultural development projects. Better grain preservation, food safety, quality management and storage efficiency result in a stronger agri-business chain, thus helping achieve sustainable agricultural development goals. As shown above, a reduction in post-harvest losses positively affects food security while quality improvements improve product competitiveness, thus increasing profits for all stakeholders involved.

AI-powered grain storage is therefore shown to play a crucial role in catalysing agricultural transformation. Through increased efficiency, decreased waste and support for food security goals, AI technologies have proven invaluable in promoting agricultural development efforts in Zimbabwe. These findings lend credence to the arguments presented by FAO (2021), World Bank (2018), Mhlanga (2014), Nhamo (2019) and Bongi and Chikozho (2020), who suggest that innovation plays an important role in advancing agriculture.

5.2.4 Conclusion regarding the Challenges and Opportunities associated with AI Implementation

This study has revealed that while AI-powered grain storage has the potential to provide many opportunities, their implementation is not without its own challenges. The lack of skills, funding and infrastructure continues to stand in the way of successful implementation. On the contrary, the potential advantages of adopting AI technologies in grain storage outweigh these challenges as is indicated by improved surveillance, efficiency, less loss of grains and greater gains experienced as a result of the application of such technology under the right conditions.

In summary, investments in human capacity building, infrastructure upgrades and other related technical services are fundamental pre-requisites in ensuring the efficacy and sustainability of the adoption of AI technology in grain storage. This research study was successful in addressing the research problem in demonstrating that AI technologies have considerable positive influence on agricultural development initiatives at GMB Kwekwe Depot. Research objectives were met, and the results obtained from the study proved empirically that AI technologies play an instrumental role in reducing grain losses, improving operational efficiency and agricultural development.

5.4 Recommendations

5.4.1 Training Programmes

Continuous training programmes focusing on enhancing the technical abilities of employees working within AI-enabled grain storage should be developed by GMB. Workshops, refreshment training sessions, and demonstrations should be regularly arranged to ensure user competence.

5.4.2 Development of AI-Enabled Storage Facilities

GMB should develop AI-enabled silos at other aggregation points and storage facilities around Zimbabwe. This would increase access to storage infrastructures, thus ensuring improved storage of grains, leading to reduced losses.

5.4.3 Improvements to Infrastructures

The Government and institutions should ensure sufficient investment is made in infrastructure, internet connections, and technology to improve the AI-enabled grain storage facilities. Without adequate infrastructure, successful implementation of the AI-powered grain storage technology is not possible.

5.4.4 Enhancing Technical Assistance Programs

Technical assistance services, such as predictive maintenance mechanisms, should be put in place for the AI-enabled storage facilities. These technical support programmes would ensure efficient operation and maintenance of the storage facility.

5.4.5 Financial Incentives for Adoption of Technology

Government bodies and development partners may wish to consider funding strategies, subsidies or other incentives that would make the costs of adopting AI-based grain storage technologies more affordable. Reduced financial burden is likely to increase adoption of AI in agriculture.

5.4.6 Formulation of AI Policies

The policy makers should come up with clear policy guidelines for the deployment, maintenance and scaling-up of the AI technologies in agricultural storage facilities. This will help in coordinating the use of technology in line with national agricultural transformation aspirations.

5.5 Contribution of the Study to Knowledge

This research makes an important contribution to the existing body of knowledge in the following ways: Firstly, through empirical data on how AI-based grain storage technologies contribute to the achievement of agricultural development programmes in Zimbabwe. Contrary to prior research studies, which have mostly explored the impact of AI on crop production and precision agriculture, the current study examines the role of AI-based grain storage technologies in enhancing agricultural development outcomes. Secondly, by identifying the links between intelligent grain storage management systems, reduction in post-harvest losses, increased operational efficiency and agricultural development outcomes.

5.6 Areas for Further Research

Focusing on the long-term economic effects of the AI-powered grain storage technologies on farmers' profitability can be a focus of future research efforts.

- The performance of AI-enabled grain storage technologies in different GMB depots or agricultural areas in Zimbabwe requires further investigation in subsequent research.
- More research is needed to explore the determinants that affect users' acceptance and intention to use AI technology in agriculture.
- Incorporating the issue of cybersecurity and ethical issues surrounding AI-powered agricultural storage technologies requires attention by future researchers.
- Comparative studies are needed to examine the performance of AI-enabled grain storage technologies compared to traditional grain storage technologies.

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APPENDIX A: RESEARCH INSTRUMENTS



BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF COMMERCE

RESEARCH TITLE:

The Impact of AI-Enabled Grain Storage on Agricultural Development: A Case Study of GMB Kwekwe Depot

RESEARCHER:

Tinashe Dangare

PART 1: INTRODUCTION LETTER

Dear Respondent,

I am **Tinashe Dangare**, a student at **Bindura University of Science Education**, currently undertaking a research study as part of my academic programme. The purpose of this study is to examine the impact of AI-enabled grain storage on agricultural development, with particular focus on the GMB Kwekwe Depot.

You have been selected as a participant because of your relevance to this study. Your responses will be treated with **strict confidentiality** and will be used solely for academic purposes. You are not required to provide your name, and participation is entirely voluntary.

Kindly answer all questions honestly and to the best of your knowledge.

Thank you for your cooperation.

Yours faithfully,
Tinashe Dangare

PART 2: QUESTIONNAIRE

SECTION A: DEMOGRAPHIC INFORMATION

Please tick (✔) the appropriate option.

Gender:

☐ Male ☐ Female

Age Group:

☐ Below 25 ☐ 25–34 ☐ 35–44 ☐ 45 and above

Category:

☐ GMB Employee ☐ Farmer

Level of Education:

☐ Primary ☐ Secondary ☐ Diploma ☐ Degree ☐ Postgraduate

Years of Experience:

☐ Less than 5 years ☐ 5–10 years ☐ Above 10 years

SECTION B: AI-ENABLED GRAIN STORAGE

(Please indicate your level of agreement using the scale below)
1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Statement	**1**	**2**	**3**	**4**	**5**
AI technologies are used in grain storage at GMB	☐	☐	☐	☐	☐
AI improves monitoring of grain conditions	☐	☐	☐	☐	☐
AI reduces human error in storage processes	☐	☐	☐	☐	☐
AI systems improve decision-making in storage management	☐	☐	☐	☐	☐

SECTION C: POST-HARVEST LOSS REDUCTION

Statement	1	2	3	4	5
Grain losses have reduced due to improved storage	☐	☐	☐	☐	☐
AI helps in detecting spoilage early	☐	☐	☐	☐	☐
Pest and moisture control has improved	☐	☐	☐	☐	☐
Storage technologies have increased grain quality	☐	☐	☐	☐	☐

SECTION D: OPERATIONAL EFFICIENCY

Statement	1	2	3	4	5
AI improves efficiency in grain handling	☐	☐	☐	☐	☐
Storage processes are faster with AI systems	☐	☐	☐	☐	☐
Costs of storage operations have reduced	☐	☐	☐	☐	☐
Resource utilisation has improved	☐	☐	☐	☐	☐

SECTION E: AGRICULTURAL DEVELOPMENT

Statement	1	2	3	4	5
Improved storage increases farmer income	☐	☐	☐	☐	☐
Food security has improved	☐	☐	☐	☐	☐
Market access has improved due to better storage	☐	☐	☐	☐	☐

Statement	**1 2 3 4 5**
Agricultural productivity has increased	☐ ☐ ☐ ☐ ☐

SECTION F: OPEN-ENDED QUESTIONS

What challenges do you face in grain storage?
……

How can AI improve grain storage systems?
……

What recommendations would you suggest for improving storage systems?
……