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DEPARTMENT OF SUSTAINABLE DEVELOPMENT

FARMERS' PERCEPTIONS ON THE ADOPTION OF ARTIFICIAL INTELLIGENCE FOR OPTIMISING AGRICULTURE IN CHINHOYI, ZIMBABWE.

BY

VANESSA MAGEVA B223991B

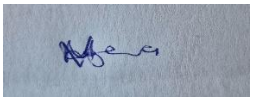
A DISSERTATION SUBMITTED TO BINDURA UNIVERSITY OF SCIENCE EDUCATION IN PARTIAL FULLFILLMENT OF THE REQUIREMENTS OF THE BACHELOR OF SCIENCE HONOURS DEGREE IN DEVELOPMENT STUDIES

SUPERVISOR: DR. E. PEDZISAI

JUNE 2026

DECLARATION

I Vanessa Mageva declare that this dissertation is my original work. It is being submitted for the partial fulfillment of the degree of Bachelor of Science Honours in Development Studies at Bindura University of Science Education. All references used in this work have been appropriately cited and acknowledged in the reference list.

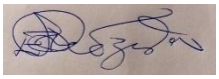
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SUPERVISOR APPROVAL FORM

The dissertation on Farmers' Perceptions on the Adoption of Artificial Intelligence for Optimising Agriculture in Chinhoyi, Zimbabwe, by Vanessa Mageva (B223991B) has been approved by me, as the supervisor for the project.

Superviser's Name: Dr E. Pedzisai

Signature:  Date: 12/08/2026

Chairperson's name: Dr Bowora

Signature:  Date: 12/08/2026

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DEDICATION

This research is dedicated to my family for their constant, enduring, loving and continuous support, encouragement, understanding and patient perseverance in everything, but particularly for their unshaken confidence in my ability to achieve my goal. It was indeed a privilege to serve this purpose for them.

ABSTRACT

Artificial Intelligence is revolutionising agriculture on a global level, through the use of forecasting, monitoring and smart irrigation. However, smallholder farmers in rural Zimbabwe are completely excluded from this digital revolution. There has been research into the technological and economic nature of AI, but little has explored how these future technologies are perceived by communal farmers in Chinhoyi. This is a qualitative descriptive case study, which sought to investigate the factors influencing farmers' attitudes toward the adoption of AI for the optimisation of agricultural production in Chinhoyi, Zimbabwe. The study was conducted in Chinhoyi town, surrounding farming fields of Makonde District, Mashonaland West Province, where tobacco, soya beans, maize and cotton are predominantly grown. The study employed semi-structured interviews, with 25 farmers, focus groups with 2 groups of farmers, observations at the fields, as well as key informants with 3 Agricultural extension officers. The data was analysed using the Braun and Clark's six phased thematic approach to analysis. 80% of the farmers had heard of AI but understood it very minimally; the highest level of penetration was in weather mobile application (72%). The level of adoption of advanced AI technology for now is at an extremely low 12%, with adoption only occurring on the side of commercial farmers while 64% of farmers were found to be using advanced AI like weather mobile application and WhatsApp agricultural advice. Farmers expressed extremely positive attitudes towards the adoption of AI with 72% of farmers willing to adopt, and high desired values were placed in using pest and disease detection technologies (87%) and advanced weather forecasting (83%). It was discovered that resistance to AI was not due to farmer apathy and resistance to innovation but rather structural barriers in accessing these technologies such as training (88%), affordability (72%) and lack of good internet access (60%). Subsidised pest detection pilots and extensive training for Agricultural extension officers coupled with a new Shona user interface could significantly improve farmer adoption of AI in Zimbabwe.

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LIST OF ACRONYMS

AI Artificial Intelligence

ARDAS Agricultural and Rural Development Advisory Services

CSIS Centre for Strategic and International Studies

DOI Diffusion of Innovations (Theory)

DRC Democratic Republic of the Congo

FGD Focus Group Discussion

HA Hectors

ICT Information and Communication Technology

IoT Internet of Things

ML Machine Learning

NGO Non-Governmental Organisation

PEOU Perceived Ease of Use (Technology Acceptance Model construct)

PU Perceived Usefulness (Technology Acceptance Model construct)

PVO Private Voluntary Organisation

SDG Sustainable Development Goal

TAM Technology Acceptance Model

CHAPTER ONE: INTRODUCTION OF THE STUDY

1.1 Introduction

This is the initial introductory chapter of this study that aims at evaluating farmer perceptions on the uptake of AI for agricultural productivity enhancement in Chinhoyi, Zimbabwe. The chapter will start with a background to the study. Following the background, the statement of the problem will be formulated in which the gap between what AI promises and how farmers in Chinhoyi, Zimbabwe perceive its deployment will be highlighted. The chapter will also present the significance of the study in relation to academic, policy, community and practitioner contribution. Subsequently, the aim, objectives, research questions and delimitations of the study will be outlined. In conclusion, the chapter will provide operational definitions of major terminologies used throughout the dissertation, such as AI, adoption and perceptions; the introduction of which leads to the literature review that is presented in the next chapter.

1.2 Background of Study

Agriculture represents a livelihood for the vast majority of people in Sub-Saharan Africa (Sithole and Olorunfemi, 2024). It is confronted by numerous challenges. The main challenges include climate change, a growing population, declining soil quality and fluctuating market conditions. On a global level, modern digital technology such as big data and AI are transforming farming. According to Aijaz et al. (2025), a creative technology that will contribute to the enhanced and sustained supply of agriculture inputs and solutions for issues of both climate change and population rise will come from AI. In agriculture, AI consists of many applications ranging from crop yield predictive analytic, drone assisted farming surveillance, AI smart irrigation systems, and AI assisted disease diagnosis in livestock and plants (Khan et al., 2021).In view of the fact that the world's population will increase to 9.7 billion people by 2050,the implementation of the various AI technologies aimed at improving efficiency and the productivity and optimising the utilisation of resources are crucial(Oliveira and Silva,2023).

In Zimbabwe, agriculture plays a prominent role in boosting economic growth (Mhaka and Runganga, 2023). The main occupation for many people in Chinhoyi is small scale agriculture

(Mugiyo, 2024). Contrary to this idea, Kangara et al. (2024) claimed that adequate extension skills are limiting successful adoption of nutrient and climate smart agricultural practices. Consequently, Dube and Manik (2025) considered the inadequate strategies by small-scale farmers on climate change and explored the possibilities of integrating AI for resilience in Zimbabwe.AI technologies enhance farming practice through the optimisation of resource utilisation, improving crop yields, enhancing crop management and decision-making. However, the rate of adoption of AI technology is relatively low in agriculture than any other industry (Ndlovu et al, 2024). In Chinhoyi, there are concepts of digital farming implemented but there are low levels of AI technology usage. There is a gap between expectations surrounding the hype of AI and farmer views. A thorough understanding of farmer perceptions about the adoption of AI, its merits, limitations, and the associated risks is key to its success and viability.

1.3 Problem statement

Existing research on AI in agriculture often focuses on its technical and economic aspects, but rarely on how smallholder farmers in rural Africa perceive it. Without understanding farmers' perceived benefits, AI initiatives may fail to meet local needs. Therefore, it is crucial to study farmer’s perceptions of AI adoption in agriculture to create relevant and inclusive adoption strategies. Tashu et al. (2025) argues that despite the achievements of the emerging technology adoption in agriculture there still exists a gap between small holder farmers, communal farmers and commercial farmers. While commercial farmers are fast adopting these technologies, communal farmers are faced with challenges such as high cost of data and low capacity among other challenges.

1.4 Justification of study

The aim of this study is to explain the perceptions of both smallholder and commercial farmers towards the use of Artificial Intelligence technologies to improve and increase agricultural production in Chinhoyi, Zimbabwe. In particular, the study attempts to explain farmers’ perceptions of the current adoption of AI, level of knowledge on AI and readiness and intent on adopting AI which all contributes to farmer's attitudes toward the new technology. Furthermore, it also identifies perceived benefits of, risks, and challenges of AI usage. Through this, the study will produce valuable information that will enable agricultural extension

workers, policy makers, and development practitioners to foster a gender responsive and context appropriate approach in adopting and using AI among farmers in rural Zimbabwe.

1.5 Aim of the Study

To explore the factors shaping farmers' perceptions towards the adoption of AI technologies in agriculture production in Chinhoyi.

1.6 Specific Objectives

1. To identify farmers' knowledge on AI applications in agricultural practices in Chinhoyi.
2. To assess the farmers' level of adoption of AI in their current farming practices in Chinhoyi.
3. To evaluate the farmers willingness to adopt AI further into their farming activities in Chinhoyi.

1.7 Research Questions

1. What is the current level of farmers' awareness of AI technologies for farmers in Chinhoyi?
2. How have farmers adopted AI in their farming activities in Chinhoyi?
3. What is the perceived willingness of farmers to adopt AI tools into their farming practices in Chinhoyi?

1.8 Significance of study

The population increase is exerting pressure on agricultural production systems and demands for increased production to ensure food security. Currently, Zimbabwe is where social, economic and political instabilities together with climate change effects and power cuts are seriously threatening food security and rural livelihood (Dube and Manik, 2025) Despite the efforts of the government of Zimbabwe, the plans for using digital technology the adoption is low (Fundira et al.2024). Academically, the study may enrich knowledge thus improving understanding of technology adoption and its perceived risks in a developing world's agricultural setting. It will contribute to the growing but underdeveloped field of social science research on digital agriculture in Africa. The study has the potential to deliver evidence-based

insights to help shape targeted policies, subsidies and training programs that respond to the concerns of the farmers rather than assumptions and to the community, the findings will empower farmers with a structured understanding of artificial intelligence which will help them in making more informed decisions. It will highlight the need for addressing not just infrastructure but also perceived risks related to cost, training and social impact. To development practitioners, this study will inform Private Voluntary Organisations (PVOs) and extension agents about farmers' motivations and subsequently allow them to formulate effective trainings and assistance programs that will build trust and empower decision-making.

1.9 Delimitations of the study

The scope of the study is geographically restricted, it is conducted only in Chinhoyi town and the farming peri urban areas surrounding it within the Makonde District of Mashonaland West Province in Zimbabwe. Conclusions are not necessarily meant for direct extrapolation to other districts or even other provinces. Moreover, the study employs a purely qualitative descriptive case study design using semi-structured interviews, focus group discussions, and field observations. Quantitative methods, statistical analysis, or experimental designs are not used. Furthermore, data collected during this study is conducted at a single point in time and the study does not track changes in farmers' perceptions over multiple farming seasons.

1.10 Definition of Terms

For the purpose of this study, the following terms are defined:

Adoption: The integration of a new technology or practice into a farmer's existing production system after a period of evaluation and trial (Rogers et al, 2014). In this study, adoption refers to the farmer's decision to use AI-related tools in their current farming operations.

Artificial Intelligence (AI) in Agriculture: A new package of technologies, which employs smart systems to perform analysis and prediction of agriculture data and implements farming activities traditionally dependent on humans, such as predicting yields and monitoring with drones, smart irrigation, and identifying pests/diseases (Javaid et al.,2023).

Perceptions: The cognitive and affective evaluations made by farmers regarding the attributes of AI technologies, including their perceived complexity, cost-effectiveness, compatibility with existing farming traditions, and associated risks (Dahlin, 2019).

Smart farming (Agriculture 4.0): The combination of digital technologies such as the Internet of Things (IoT), artificial intelligence, robotics and drones in the production process of agriculture, to make efficient use of resources and increase the sustainability of agriculture (Silva et al. 2023)

1.11 Chapter outline

The dissertation has been structured into five closely integrated chapters to conduct a thorough investigation of farmers' perceptions towards the adoption of artificial intelligence in Chinhoyi. Chapter one provides an introduction, background and statement of the problem, objectives and significance. Chapter two reviews the literature review and covers global, continental and regional patterns of use of AI in agriculture. Chapter three describes the research design, population of the study, sample and data collection methods and tools. Chapter four discusses and presents the results derived from the research in relation to farmers' attitudes towards the adoption of AI in agriculture. The last chapter presents a concluding summary, conclusion and recommendations from the results, aimed at policymakers and agricultural extension services operating in Chinhoyi.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter offers a literature review on farmers' perception of AI adoption in agriculture. It identifies the theoretical and conceptual context of the study through literature on digital transformation in agriculture. The literature review will provide an attempt to connect this current research in Chinhoyi to other research concerning adoption of technology and perceived impact on agriculture. By exploring this, the chapter identifies research gaps that this study aims to fill, particularly regarding smallholder farmers in rural Africa.

2.2 Theoretical framework

Understanding farmer perceptions on the adoption of AI in agriculture requires grounding in established theoretical frameworks that explain how individuals evaluate and decide on new technologies. A theoretical framework is a blueprint of research. In this work it is the framework that will be used in analysing the perceptions of the farmers in Chinhoyi. The attempt to examine what farmers in Chinhoyi think about AI has to go beyond simple description and employ well established behavioral models which indicate what factors determine human behavior.

2.2.1 Diffusion of innovations theory (DOI)

This study will use Rogers' Diffusion of Innovations (DOI) framework to see AI as a social process, not merely a technical one. This theory helps in identifying potential influential variables for the adoption of a method (Mustonen and Lyytinen, 2003) The DOI distinguishes different kinds of adopters from innovators to early adopters, early majority, late majority and laggards according to their willingness to adopt change (Kaminski, 2011). While the innovators in Chinhoyi are likely the larger commercial farmers with the capital to take on the financial risk of using a new AI driven soil sensors or drone surveillance technology, the bulk of smallholders in the district are likely to be late adopters, reluctant to invest their limited resources until local evidence of the success of such technology is readily observable.

According to DOI five features influence an innovation's rate of adoption (Park et al., 2022). They are relative advantage (the degree to which the innovation is superior to what it

supersedes), compatibility (how well it fits with the existing culture and needs of adopters), complexity (the degree to which it is difficult to learn and use), trialability (how easily it can be tested on a limited basis), and observability (the extent to which others can see its benefits). In rural Zimbabwe, the compatibility of the AI with existing rural cultures and existing routines of farming and weather prediction are very important. An AI which recommends farming routines out of sync with traditional lunar based cycles or local weather beliefs, without providing a convincing explanation, is likely to face a high degree of complexity barriers. Sithole and Olorunfemi (2024) argue that for sustainable agricultural practices to spread, they need to be compatible with farmers' immediate livelihood and economic conditions.

The opinion leader whether an influential farmer in the local community or an agricultural extension worker in the area, plays a key role in spreading innovation. When an opinion leader successfully deploys the AI technology to avert disaster during a severe drought in Chinhoyi, observability is triggered and word begins to spread throughout neighboring farmers. However, Dube and Manik (2025) warn that if the supporting technological infrastructure like regular electricity and cell phone coverage is not available, the most obvious success will only diffuse to the tiny elite who can already afford and benefit from modern technology.

Lastly, the DOI framework itself notes that innovation can diversify, that the rich and the poor move farther apart. The risk with AI application in Zimbabwean agriculture is that benefits could flow more easily to those who have schooling and financial capital, marginalizing communal farmers even further. We will review the DOI theory to find how information is disseminated through social networks in Chinhoyi and to identify where the diffusion process breaks down. This information will help in developing inclusive adoption strategies to ensure that AI becomes accessible to all, not just the affluent.

2.3 Conceptual framework

This framework shows the variables to farmer perceptions and finally to the adoption of Artificial intelligence in Chinhoyi. It brings together the concepts from the Diffusion of Innovation theory. Moreover, it explains the relationships between the theory and their impact on farmer adoption of technology. The structure indicates, from top to bottom, the external factors related to the context of Zimbabwe: digital infrastructure, costs of the AI tool, and access to agricultural extension. These three constructs have an impact on the two major psychological influences of the model: Perceived usefulness (PU) and Perceived ease of use

(PEOU).These two psychological influences are formed in context, and are mediated by the user's personal characteristics, such as a farmer's age and level of education.(Creswell and Creswell, 2017).

Conceptual Framework Diagram

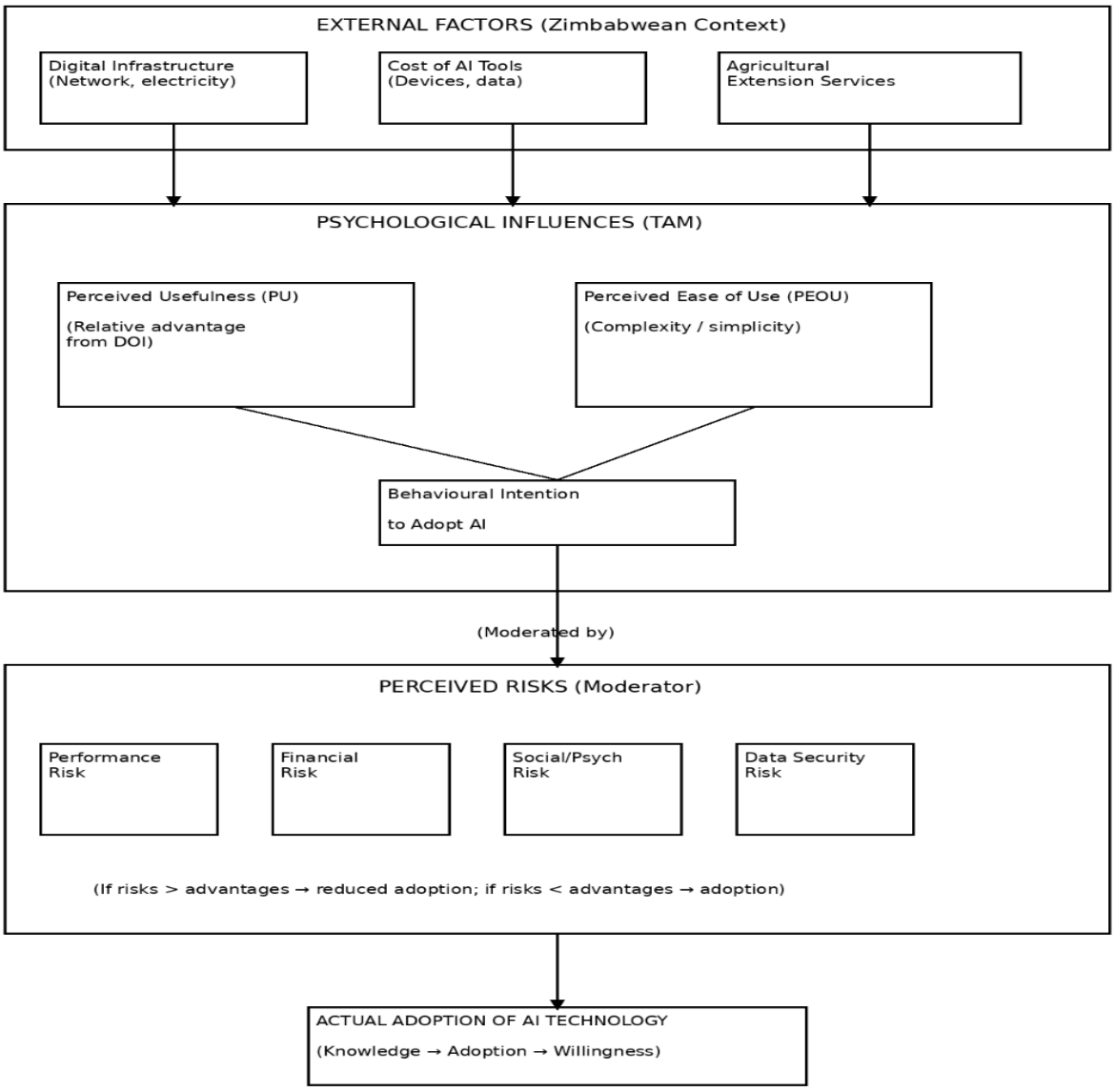


Figure2. 1: Conceptual Framework

2.4 The evolution and conceptualisation of AI in agriculture

By adopting digital technologies in agriculture the process changes towards what it is known as Agriculture 4.0 or smart farming (Silva et al., 2023). These technologies, as digital technologies themselves, are able to achieve sustainability from social and environmental point of view (Costa et al., 2023).This trend integrates technologies such as Internet of Things (IoT), Artificial Intelligence (AI), robotics, drones to maximise agricultural productivity and sustainability. With AI being one of the fundamental technologies. As the literature mentions, AI refers to a set of technologies composed of machine learning (ML) based prediction analytics and computer vision based image recognition that can improve the climate resilience and sustainability of agriculture by enhancing crop monitoring, early warning for drought and floods and monitoring for pests and diseases (Sarun et al., 2026).

2.4.1 Available AI tools

Between 2024 and 2026 there was rapid growth in the kinds of AI tools available, ranging from expensive robotics to inexpensive data driven applications accessible to smallholders in the Global South (Maslej et al., 2025).From remote sensing through to machine learning a primary tool in the utilisation of remote sensing data for monitoring the UN's SDGs in rural areas (Klingwort et al., 2026). Regarding Zimbabwe specifically, particularly the farming clusters in Chinhoyi, AI tended to present as mobile based prediction services, remote sensing feed and automated advisory platforms. Site specific, visually inaccessible information such as pest and disease detection and nutritional deficiency, could be identified through machine learning/algorithms to analyse the spectral data provided by the satellite driven crop monitoring system allowing farmers to forecast issues and apply remedies accordingly. Eco Farmer which provides weather forecast and agronomic advice to farmers using mobile phones by region, Mudhumeni Muhomwe an AI driven local platform follow suit. Beyond such applications, aerial spraying and mapping using drones offered another more tangible form of AI, with these technologies interconnected as part of an integrated digital system to move agriculture from practice to real-time algorithmic precision.

2.5 Farmers awareness and digital literacy

The degree to which farmers have heard of, seen or been exposed to specific Artificial Intelligence application in agriculture varies. In most cases it is often uneven with some farmers knowing about drones but not about AI- driven soil analysis. Farmers' awareness and digital literacy stand as the primary conditions for the adoption of Artificial Intelligence within Chinhoyi's agricultural sphere. Closely connected to this notion is digital literacy. Digital literacy is the ability to navigate, evaluate and create information via digital technologies (Martin and Grudziecki, 2006) .Levels of digital skills include basic skills, internet skills, media literacy, data literacy, information literacy, social media literacy, cyber security awareness and digital communication skills (Mensah et al., 2024).It goes beyond awareness towards the capacity to explore digital menus and read data driven findings. In rural Zimbabwe where the digital gap widens under high data prices and unreliable network services, digital literacy becomes a problem. If the farming population in Chinhoyi falls short of the technical know-how needed to engage with AI driven platforms, their views of the technology will stay muted despite the possible gains in yield the system could provide. Some rural, less educated farmers are ignorant of harmful practices and this ignorance is attributed to their inability to access information at the right time. Consequently, farmers develop an inertia towards adopting new technologies for farming (Javaid et al., 2023). Farmers' ignorance and lack of both awareness and digital literacy serves as a hindrance to the adoption of agricultural-based technologies and innovations that have the potential to revolutionalise agriculture (Mensah et al., 2024).

2.6 Utility of AI in farming

The role of AI in farming has shifted from an additional benefit to a core driver of productivity and climate adaptation.AI has been cited as a key agent for the legitimation of agriculture. Examples of roles of AI in farming include precision decision support, early warning systems and climate resilience, conversational interfaces and advisory support, precision agriculture and resource optimisation,crop health and disease prediction.

2.6.1 Global perspective

Digitisation of agricultural inputs and resource optimisation are taking place globally through big data and AI. Aijaz et al. (2025) believe that with dual strains of climate change and increasing world population, it will only be possible to maintain crop production through the use of AI. Agriculture is the sole means of sustenance for the sub Saharan Africa. However,

the region has peculiar challenges of degrading soils and unstable markets, which Sithole and Olorunfemi (2024) state have often delayed the adoption trends of sustainable practices among smallholders. Use of AI in modern farming is in data driven decision making; with AI integrated with the Internet of Things (IoT) sensors, farmers move from field level farming to sub meter level (Manono, 2026). AI algorithms, fed with inputs from soil moisture sensors can help automate irrigation to cut water wastage but not compromising plant water levels (Abdelmoneim et al., 2026). Other forms of AI in farming analyse the pH level of the soil, to ensure the correct ratio of nutrients and thereby reduce waste of fertilizers applied only where deficiency of a particular nutrient exists (Devika et al., 2025).

Data collection and storing has also been evolved through AI platforms to on the go computation. Instead of relaying the data to cloud servers and analysing, models can be fitted in drones and sensors themselves enabling site-specific application of agricultural inputs.(Kakiz, 2026).An example is John Deere's See and Spray , which is programmed to distinguish weeds from crops using computer vision within milliseconds thus saving 70% chemicals (Dimitris et al., 2025). Use of AI in the early warning systems and climate resilience is another area which seems crucial. With climate related shocks estimated to increase crop yields by 10–20% by 2050, the utility of AI lies in using predictive modelling and geospatial analysis (Gambelli, 2024). With early warning systems which analyse possible threats, it is possible to take proactive measure of adjusting planting calendars (Kumari et al., 2025). The use of AI in conversational interfaces and advisory support to farmers cannot be overemphasised, digital green's farmers chat used a large language model to provide easy to understand advisory services thus scaling agricultural extension which was previously limited due to human resources (Ochar et al., 2025).

2.6.2 Continental

At the continent and sub continental level the value of AI in agriculture will be differentiated through the adoption of a transition from subsistent to precision agriculture. In Northern Africa The key values derived from the application of AI are to increase water use efficiency and climate change adaptation. Given the chronic water crisis currently experienced by both Egypt and Tunisia smart irrigation with AI has been prioritised (Ramat et al., 2023). Egypt is utilizing AI to enhance its agriculture through thermal imaging and IoT sensors in order to assess evapotranspiration. This has led to the deployment of smart irrigation where farmers will apply water only after the AI systems detect specific biochemical markers of water stress. As such

Egypt has become a major technology hub with a rapidly growing number of agritech start-ups going from 3 in 2022 to 11 in 2025 (Tarek et al., 2025).

Moving to Southern Africa countries such as South Africa and Botswana lead in terms of high value crop analytics and digital finance. South Africa boasts aerobatics which uses both AI-powered drone imagery and computer vision to conduct a per tree analysis of crops in orchards. As such, citrus and macadamia farmers are able to detect pest infections and nutrient deficiency in their farms before they spread throughout the entire farm (Ojo, 2024). Both Botswana and South Africa have applied AI to analyse spatial data, generating credit scores for stallholder farmers who have no formal collateral but are able to demonstrate a healthy crop through an AI analysis (Ndhlovu and Chidoko, 2026). These two countries are also at the forefront of the adoption of AI and geospatial technologies. The deployment in agrifood systems is now reaching what indicators have shown is possible .Lastly Central Africa countries are at their earliest stages of AI adoption, focused on predictive modelling and mapping, although this region possesses high levels of hunger as well as land potential . In the DRC start-ups such as Yamify are now utilising AI to implement predictive modelling that will aid in the classification of crops and monitoring soil health.

2.6.3 National

Within Zimbabwe AI has been integrated as a cornerstone of the Agriculture Food Systems and Rural Transformation Strategy. The overall characteristic of AI usage within Zimbabwe involves providing localistic precision through the implementation of generalised climate warnings, to localised field specific digital recommendations that can mitigate the risks associated with unstable rainfall and degraded soil through predictive analysis. Also tobacco, which has been historically handled through a manual, subjective process, is being handled with AI based computer vision systems which create stability in its grading based on the characteristics of cured leaves colour, texture and size resulting in farmers getting appropriate prices for their crops (Ndhlovu and Chidoko, 2026). In parallel with this, Zimbabwe is also using AI driven satellite data that assists national program initiatives in producing digital recommendations for the Pfumvudza/Intwasa program. The computer models can predict the occurrence of a false start of a rainy season so that farmers do not waste resources on seed and fertilizer if a rainy season fails early (Begho, 2025).

2.7 Challenges of the available AI tools

In as much as AI offers many benefits its adoption remains uneven. Smallholder farmers face significant challenges which include high costs, limited infrastructure and lack of specialized digital literacy (Gardezi et al., 2024). Equally important, the lack of data governance frameworks and limited interoperability of datasets in rural areas continues to constrain the full deployment of AI solutions in developing regions (Lokonon et al., 2026).

2.8 Research gap

While extensive research focuses on the technical and economic performance of AI, there is a marked deficiency in social science research regarding digital agriculture in Africa. Current literature often ignores how smallholder farmers in rural settings in Chinhoyi actually perceive these tools. Most of the literature in Chinhoyi has examined the effects of general technology usage on productivity instead of the psychological and social variables that influence AI perception. This research will not only focus on technical measures, but rather generate evidence-based understanding of farmer intentions and perceived risks thus filling a knowledge gap in the Zimbabwean context.

2.9 Chapter summary

The reviewed literature also demonstrates that while the technological aspect of AI in agriculture has the potential to foster sustainability, the actual use of the technology depends upon farmer readiness and perceptions, and the significant difference between commercial and smallholder use further indicates that inclusionary strategies need to take local perceptions into consideration. The following chapters will detail the methodology used to capture these nuanced perceptions in Chinhoyi, Zimbabwe.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the research methodology and strategies that have been utilised to investigate the farmer's perceptions on AI adoption in Chinhoyi will be discussed. A strong methodology is required to ascertain validity and replicability of any given research to the academic world as it suggests (Hirose and Creswell 2023). In this project the methodology used is a qualitative method, it will allow the researcher to investigate farmers' perceptions and views on AI adoption at great length, without conducting complex statistical analysis of the data. Furthermore, the chapter will explain the method used along with research design giving valid reasons as to the use of an interpretivist paradigm and qualitative approach when considering the issue of technological adoption, (Saldana, 2021). Finally the chapter will describe the location of the study area, sample, population and how the data was gathered and how the data was analysed.

3.2 Study area

The research was conducted in Chinhoyi which is a city and administrative centre in Mashonaland West Province of Zimbabwe. This city together with the neighbouring area in Makonde district covers roughly 8680 km2 (Tarusarira and Maviza, 2025) with strong agricultural foundation. Smallholder farming is prevalent and maize and cotton are grown in majority (Mugiyo, 2024), while households also grew groundnuts during rainy seasons (Muzanenhamo et al., 2024).The agricultural regions where Chinhoyi are situated fall within Natural Region II and III which are characterised by moderate high rainfalls but are increasingly subjected to short dry spells between mid-season, changing rainfall patterns. In terms of land use structure, Chinhoyi is composed of commercial large-scale farms and communal smallholder lands. In small holder farming, rain-fed agriculture dominates the sector thus ensuring food security to local populations. Agriculture is an important source of livelihood and revenue in the region (Mugiyo, 2024). In terms of type of agriculture, most activities is under smallholder cultivation of staples, and cash crops such as maize and cotton. This agricultural setting, despite being potentially profitable is faced with challenges mainly due to soil erosion, lack of access to enhanced digital technologies and dependence on old

conventional practices and hence, requiring studies of artificial intelligence adoption in its agriculture.

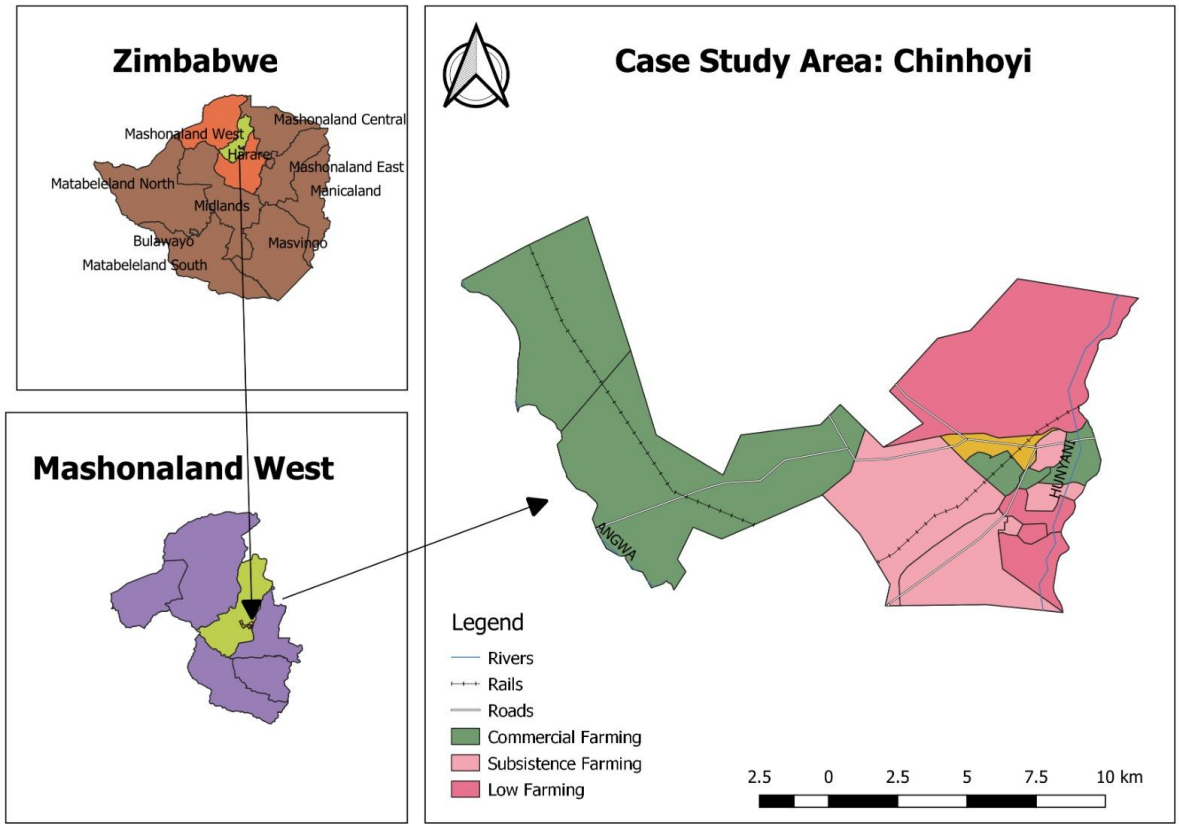


Figure3. 2: Chinhoyi Study Area Map (Source Quantum Geographic Information Systems Software)

The design chosen in this research to investigating and understanding the factors affecting farmer attitudes toward AI adoption in Chinhoyi was the Descriptive Case Study Design. The Descriptive case study design allowed detailed investigation of a particular region's agricultural communities in their natural setting (Johnson et al., 2025). As Yin (2018) pointed out, a case study is an empirical inquiry that investigates a contemporary phenomenon within its real world setting where the boundaries between the phenomenon and its context are not readily apparent.The qualitative data of farmers' perception towards AI were collected and analysed using descriptive case study approach to describe vividly the current situation of digital readiness in Chinhoyi. Baxter & Jack (2008) states that a case study method is of great benefit for issues which are influenced by various factors such as infrastructure, education and culture.

3.4 Target population

The target population for this study consists of the diverse community of agricultural producers who live and farm in Chinhoyi, Makonde District. This population represents the broader range of the Zimbabwean agricultural sector; from communal small holder farmers practicing subsistence agriculture to large scale commercial farmers utilising irrigation schemes and mechanised production systems. A broad range of agricultural producers in this area are included in the sample to ensure comprehensive mapping of the views towards Artificial intelligence and inclusion of respondents with various education levels, age groups and exposure to technologies (Muzanenhamo et al., 2024). Emphasis is placed on household heads and farm managers because they are generally decision-makers with respect to adopting a new practice, making financial investments in new technologies, and also key informants such as extension workers from the Department of Agricultural and Rural Development Advisory Services (ARDAS). Extension workers have significant institutional knowledge concerning prior adoption patterns and socio-economic factors affecting farmers' behaviour (Tashu et al., 2025).

3.5 Sampling

3.5.1 Sampling technique

Purposive sampling technique was employed in the selection of the participants. Purposive sampling is non probability method which the researcher deliberately selects participants with certain qualities deemed relevant to the topic. The researcher is using their judgment to select participants that they believe would be the most useful for the study as stated by Creswell and Creswell (2017). The use of this technique makes it possible to purposefully hand pick participants to contribute the richest data to answer the study's question as supported by Saldana (2021), who further elaborated that purposive sampling is a well-known technique in qualitative inquiry because it can be the most efficient technique to pinpoint and hand select relevant rich data cases. The selection process of purposive sampling was done on three levels: Farmers who reside and farm in Chinhoyi were the desired group of people. Second, both small holder and commercial farmers were chosen to reflect a range of opinion towards adoption of technology, and third extension officers were considered an expert group familiar with agricultural technology adoption in the area.

3.5.2 Sample size

Below is a breakdown of the respondents in terms of categories and numbers. Small holder farmers 12-15, Commercial farmers 8-10, Agricultural extension officers 3-5 with a total of 25-30. Sample size was in agreement with recommendations from qualitative research scholars, and it is recommended that between 5 and 25 respondents provide enough data for phenomenological or case study research, where saturation of data is likely to have been reached by this point in the analysis (Creswell & Poth, 2021). In a Focus Group Discussion setting, Krueger & Casey recommend a total sample size ranging between 6 to 10 participants per group (Saldana, 2022).

3.6 Data

The research will utilise semi-structured interview guides as the primary tools for data collection. These instruments enable the researcher to systematically gather in-depth insights into farmers' perceptions, technological readiness, and the specific socio-economic challenges related to the adoption of Artificial Intelligence (Kumar et al., 2021). By employing semi-structured guides, the researcher can maintain consistency across various participants in Chinhoyi while allowing for the necessary flexibility to explore individual experiences and local knowledge (Saldana, 2022). This adaptability is crucial for understanding the nuanced factors that either hinder or facilitate the transition from traditional to digital farming practices (Creswell and Creswell, 2023).Furthermore, these guides are designed to capture the social and behavioural dimensions of technology adoption, providing a comprehensive view of how rural households perceive the risks and benefits of algorithmic decision-making in their daily operations (Mwangi and Wainaina, 2022). As noted by Tashu et al. (2025), the use of detailed interview prompts allows for the discovery of hidden barriers, such as lack of trust in data privacy or the perceived threat to traditional labour roles, which standardised surveys might overlook. Ultimately, the use of interview guides ensures the collection of rich, contextualised data that accurately reflects the realities of Chinhoyi's agricultural landscape (Sithole and Olorunfemi, 2024). This qualitative depth is instrumental for interpreting the quantitative trends found in the study and will serve as a foundational guide for the development of targeted policy interventions and support mechanisms for inclusive digital transformation in Zimbabwe (Chirwa and Mlambo, 2023; Muzanenhamo et al., 2024).

3.7 Data Collection Instruments

Following a qualitative research approach three key instruments were utilized:

3.7.1 Semi-structured interview guide

The semi-structured interview guide was the principal instrument used in individual interviews with both farmers and extension officers. The instrument is designed to collect in-depth and holistic perspectives on farmers' technological readiness, their current level of engagement with AI technology and their specific circumstances and the associated socio-economic factors concerning adopting AI technology (Kumar et al., 2021). Using a semi-structured guide allowed the researcher to maintain a degree of consistency in questioning across participants while allowing for flexibility to explore various responses and personal stories relevant to the context of farming in Chinhoyi (Saldana, 2022). It accommodates the flexibility that is critical in collecting nuanced information about enabling and constraining factors affecting farmers' move toward modernizing farming (Creswell & Creswell, 2017). The interview guide was developed in four sections following the research objectives: (A) Profile of the farmers and respondents, (B) Knowledge of AI applications, (C) Current status of AI adoption, and (D) Willingness to further adopt AI. In line with the study by Tashu et al. (2025) a guide will help the researcher to gather detailed information where barriers such as trust in data, labor loss, and other cultural or institutional obstacles can be uncovered.

3.7.2 Focus group discussion (FDG) protocol

Focus group discussions with smallholder and commercial farmers separately will be held in order to facilitate data interactivity and capture perceptions and collective concepts about AI. Focus group discussion is an appropriate technique in rural Zimbabwe because it allows researchers to examine the role of the social norms on behaviour of innovation adoption (Sithole and Olorunfemi, 2024). Each group is expected to consist of 6-8 people and each discussion should last for an estimated 40-60 minutes.

3.7.3 Field observation checklist

A structured observation checklist will be used during farm visits to record the presence and level of use of technology related devices such as mobile phones, access to internet and the use of smart systems such as irrigation and other software. This data will be used to supplement

information collected from interviews and FGD's and also to provide corroborating evidence, hence enhancing validity (Tashu et al., 2025).

3.7.4 Data collection methods

Data will be collected using qualitative methods comprising of semi-structured interviews, Focus Group Discussions (FGDs) and observation. These are crucial for understanding the reasoning behind the numbers. These methods prioritise the how and why, allowing farmers to articulate their concerns regarding data privacy, job displacement, or cultural compatibility in their own words (Saldana, 2021). In the rural context of Chinhoyi, qualitative inquiry is vital for uncovering the nuanced social dynamics and traditional values that influence technological trust (Muzanenhamo et al., 2025).

3.8 Data collection procedure

The planned data collection exercise will unfold through a deliberate multi-phase design to secure high-quality information from farmers in Chinhoyi. It begins with an opening stage involving early visits to the district's agricultural extension offices and other relevant authorities where the team will present research clearances, explain the study goals, and obtain official consent and logistical backing to enter farming communities. Subsequently, the researcher will hold community sensitisation meetings in each chosen area engaging village heads and local leaders to outline the project, ease initial doubts, and create conditions favourable to farmer participation. Actual data gathering will proceed as trained research assistants administer the interviews at farmer’s homes or fields, appointments set for times that suit respondents so farming routines stay largely undisturbed. Concurrently, Focus Group Discussions will be arranged on mutually agreed dates, with purposively selected participants to guarantee diverse representation, and every session led by a moderator and supported by a note taker who captures spoken contributions as well as gesture and tone.

3.9 Data analysis

Interviews and FDGs data will be analysed through thematic analysis, which is a type of qualitative data analysis method used to identify, analyse and report pattern or themes across qualitative data (Saldana, 2021). This type of analysis has been chosen because it gives the

researcher flexibility to use rich data from the farmers and still be able to be methodical and structured while analysing it.

3.10 Validity and Reliability

In this qualitative study, trustworthiness was established to ensure validity and reliability. The study's validity and reliability will be assessed using a pilot study in a neighbouring district to check for consistency in how questions are understood. Credibility will be established through triangulation, where the researcher compares findings from farmers with those from extension officers (Saldana, 2021). Furthermore, member checking will be used, where the researcher returns to select participants to confirm that the transcribed summaries accurately reflect their views. Dependability will be maintained through a clear audit trail of field notes and recordings, ensuring the research process is transparent and reproducible (Johnson et al., 2025).

3.11 Ethical considerations

All potential participants, comprised of commercial and small holder farmers as well as extension officers in Chinhoyi, shall be fully informed about the research project, the purpose and objectives of the study prior to data collection. Participants are not obligated to take part in the study, and it will be possible for a participant to withdraw from the research at any point without being penalised (Sarvestani, 2026).Moreover, no personally identifying information such as participant's names or precise farm coordinates shall be recorded. All research participants shall be given pseudonyms, such as "Farmer A" or "Extension Officer 1". Research materials shall be stored in a locked drawer in offices and password-protected in digital format. The researcher shall respect the local customs and traditions and accommodate to farming schedules and study convenience time with each of farmer and extension worker.

3.12 Limitations of the study

This study looks at only one city within a district, its lessons may travel poorly to places that farm in other ways, follow other social customs, or rely on other levels of digital tools. Secondly, the project leans on self reported talk from interviews and focus group chats, which opens the door to social desirability bias, so participants might say what they think sounds right instead of what they truly feel, especially when the topic is a new idea like artificial intelligence. Thirdly, the cross sectional design freezes opinions at one moment, leaving no room to see how

those opinions might shift as knowledge of AI spreads or as fields and climates shift. Fourthly, words and translation can trip up the process during both data capture and later review, since terms tied to artificial intelligence often lack neat matches in local speech, and slight shades of meaning can slip away or twist. Additionally, rough access to some farm areas, more so in the heavy rains when tracks turn into mud, can fence off parts of the population and trim the mix of voices heard. Finally, the current low reach of AI knowledge among smallholder farmers in rural Zimbabwe means that answers may lean on guesswork rather than lived practice, which may thin the depth and reach of the insights.

3.13 Chapter summary

This chapter explained the methodological framework that will be used to study farmers' attitudes toward adoption of AI technology. It provides a justification for adopting qualitative methods in the research, explains the descriptive case study design used, identifies the site and participants of the study, describes the purposive sampling method, data collection methods and a detailed explanation on how the data will be analyzed, through thematic analysis, supported by rigor factors and ethical considerations. Chapter 4 will present the findings based on the above methods.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Introduction

This chapter outlines the analysis and interpretation of qualitative data from 30 participants in Chinhoyi, Makonde District. The qualitative data was gathered from semi-structured interviews with 25 farmers and two focus group discussions involving a total of 10 more farmers, some participants from the interviews are included again for triangulation with focus groups. The total sample of 30 participants consisted of 22 small holder farmers, 5 commercial farmers and 3 extension officers which were selected through the sampling procedure described in chapter 3 ,purposive sampling. The analysis was conducted using the thematic approach according to the three research objectives: (1) To determine the level of farmers' knowledge on the uses of AI, (2) To determine the level of AI adoption by farmers, and (3) To determine farmers' attitude towards adoption of AI. The findings are presented in form of graphs, with relevant verbatim quotations and photographs from the field followed by discussion.

4.2 Background information

This socio-demographic feature among the 25 respondents interviewed is outlined as: > 64% were males, > 36% were within the ages 41 to 50 years and 56% were having at least secondary education and 76% were smallholders farming less than 5 ha. The description is consistent with the profile of the farming population in the Makonde district where the majority of livelihoods is through rain-fed smallholder farming. The three extension agents had an average of 10 years field experience.

4.3 Demographic Characteristics

Table 4. 1: Socio-demographic characteristics of interviewed farmers'=25

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	16	64%
	Female	9	36%
Age group (years)	18–30	4	16%

	31–40	6	24%
	41–50	9	36%
	51 and above	6	24%
Highest education level	Primary	8	32%
	Secondary	14	56%
	Tertiary	3	12%
Farmer type	Smallholder (<5 ha)	19	76%
	Commercial (≥5 ha)	6	24%

Source: Field survey data (2026)

Table 4. 2: Distribution of participants by category

Participant category	**Number of participants**
Smallholder farmers	19
Commercial farmers	6
Agricultural extension officers (key informants)	3
Total	**28** (plus 2 additional in FGDs)

Note: Two additional farmers participated only in focus group discussions, bringing total unique participants to 30 as stated in Chapter 3.

Source: Sampling framework (Chapter 3, section 3.5.2)

Table 4. 3: Extension officers' professional background (n=3)

Officer code	Years of field experience	Role
EXT-01	12	ARDAS district officer
EXT-02	8	ARDAS field extension worker
EXT-03	10	ARDAS field extension worker

Mean years of experience: 10 years

Source: Key informant interviews (2026)

4.3: Farmers' knowledge of AI applications

Farmers' Awareness and Understanding of Artificial Intelligence

In general, farmers had moderate level of awareness about AI but low level of understanding. The response show that almost eighty percent of respondents have heard the term Artificial Intelligence and most farmers said that they heard the term Artificial Intelligence mostly from agricultural extension officers, social media network, and mobile based agricultural advisory services. However, in the interviewed and focus group discussions majority farmers just heard the term and have only vague idea about AI and generally take it as smart technologies. Another twenty percent farmers say that they have heard the term Artificial Intelligence only after being involved in the study.

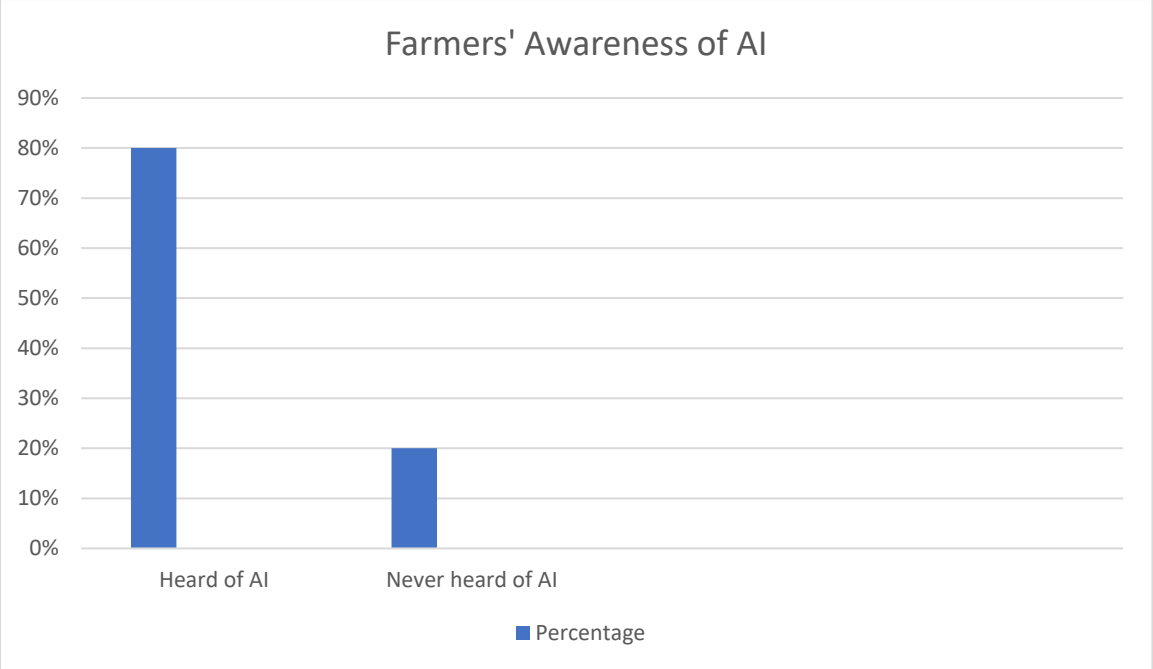


Figure 4.3: Farmers' awareness of AI in agriculture (Source Primary data)

Interpretation: This is in agreement with a lack of understanding, rather than knowledge, of the term AI amongst the farmers and is an issue where informative campaigns and training exercises targeted at the agricultural community can and should concentrate.

Most Recognised AI-Related Agricultural Tools

Respondents were asked to list all AI related technologies they were aware of or had already encountered and the findings were as follows, 72% knew what weather forecasting applications were, 28% knew what pest diagnosis applications were, 20% knew what a crop sprayer/monitoring drone was and finally 16% of respondents knew what soil sensors were.

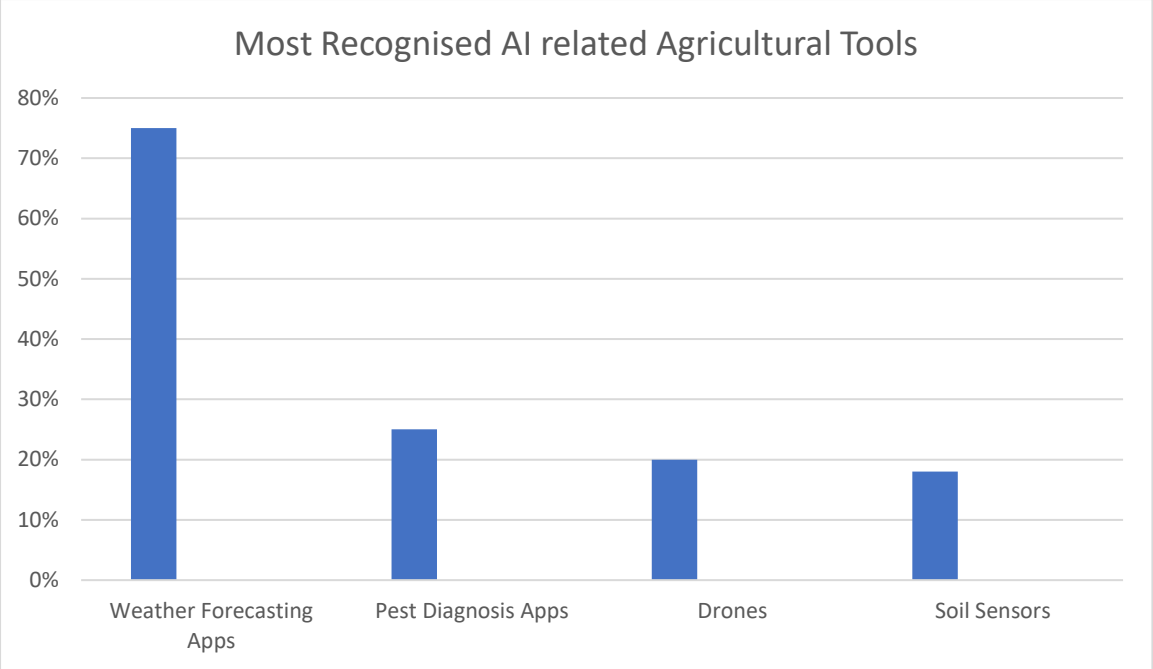


Figure 4.4: Most Recognised AI-Related Agricultural Tools. (Source: Primary Data)

Interpretation: This is in agreement with a lack of understanding, rather than knowledge, of the term AI amongst the farmers and is an issue where informative campaigns and training exercises targeted at the agricultural community can and should concentrate.

Description of pattern: A large majority of farmers have heard the word Artificial Intelligence, but this exposure has been minimal and vague, as many farmers simply associate artificial intelligence with any form of digital technology. Only among those with a minimal awareness are mobile based weather forecasting applications the most commonly known technology, with more advanced applications like drones and soil sensors being known by only a small proportion of the farming population.

Verbatim quotation (Interview):

> *"I have heard of AI on radio. They say that it is something that thinks like a human but I don't know how it can help my maize. I only use the weather forecasting application on my phone because it has saved my crops twice."*(Farmer 11, smallholder, age 48)

Farmer demonstrating a drone technology during fieldwork



Plate 4. 1: Farmer demonstrating a drone technology. (Source: Primary Data)



Plate 4. 2: Farmer demonstrating a drone technology (Source: Primary Data)

Verbatim quotation:

> *"As a farmer in Chinhoyi, I faced many challenges when it came to keeping track of my crops, especially when it came to spraying my field with chemicals. Now with drones, I can do it a lot quicker and also be more precise".* (Farmer 13, Commercial Farmer, age 38)

4.4: Farmers' level of adoption of AI in current practices

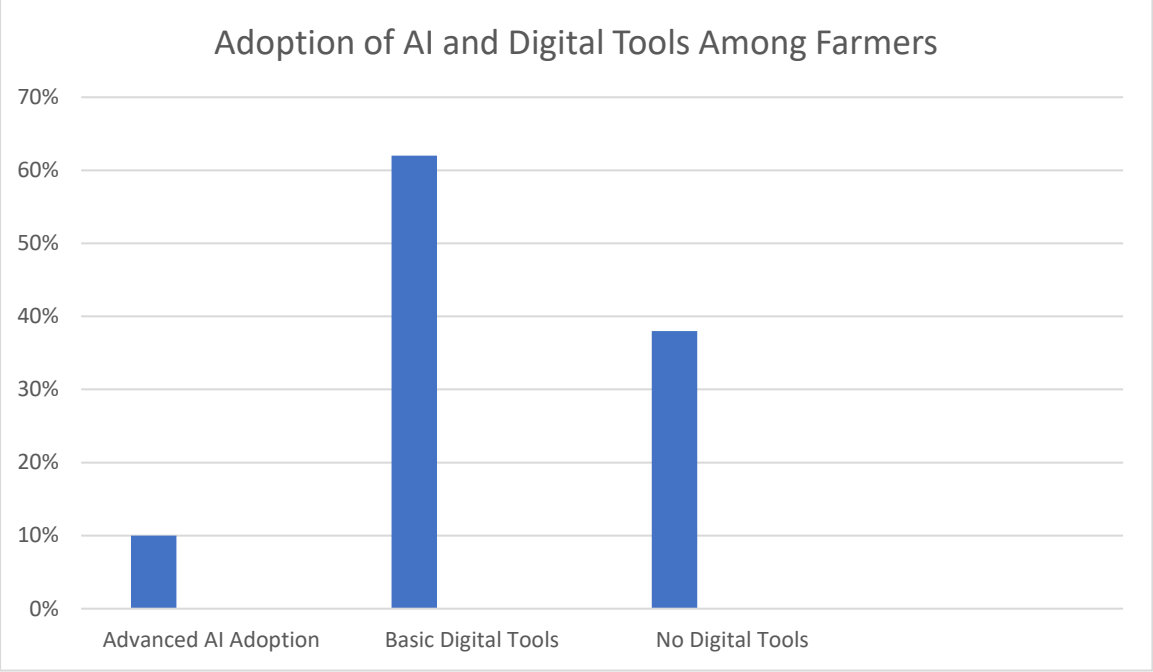


Figure 4. 5: Current adoption of AI and digital tools among farmers. (Source: Primary Data)

Farmers have a very low adoption rate of advanced AI adoption (drones, automated irrigation, AI pest detection), while basic digital tool use (weather apps, WhatsApp advisory, basic soil testing) has a fairly large percentage. The researcher also realised that not everyone is aware of AI tools as shown above.

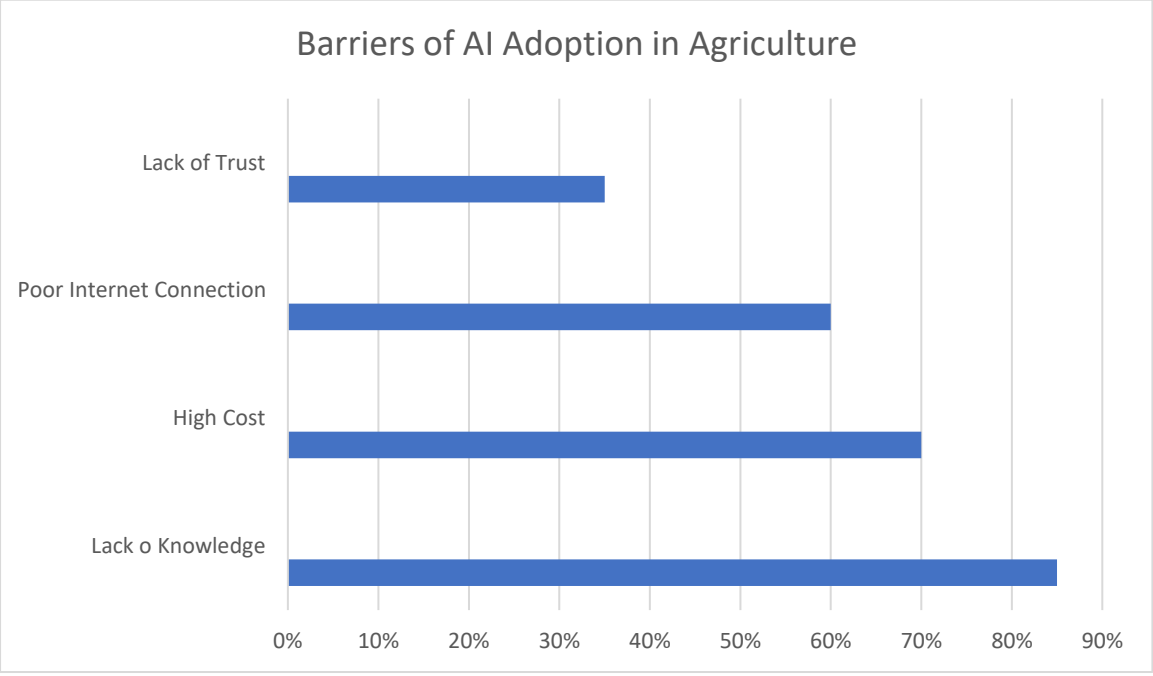


Figure 4.6: Barriers of AI Adoption in Agriculture (Source: Primary Data)

Description of pattern: Advanced AI adoption is very low and confined entirely to commercial farmers. Nevertheless, a reasonable number of farmers utilise a simple digital device that could be an access point to subsequent adoption of AI technology. It's important to note the most commonly cited obstacles (knowledge, costs), network, followed by lack of trust.

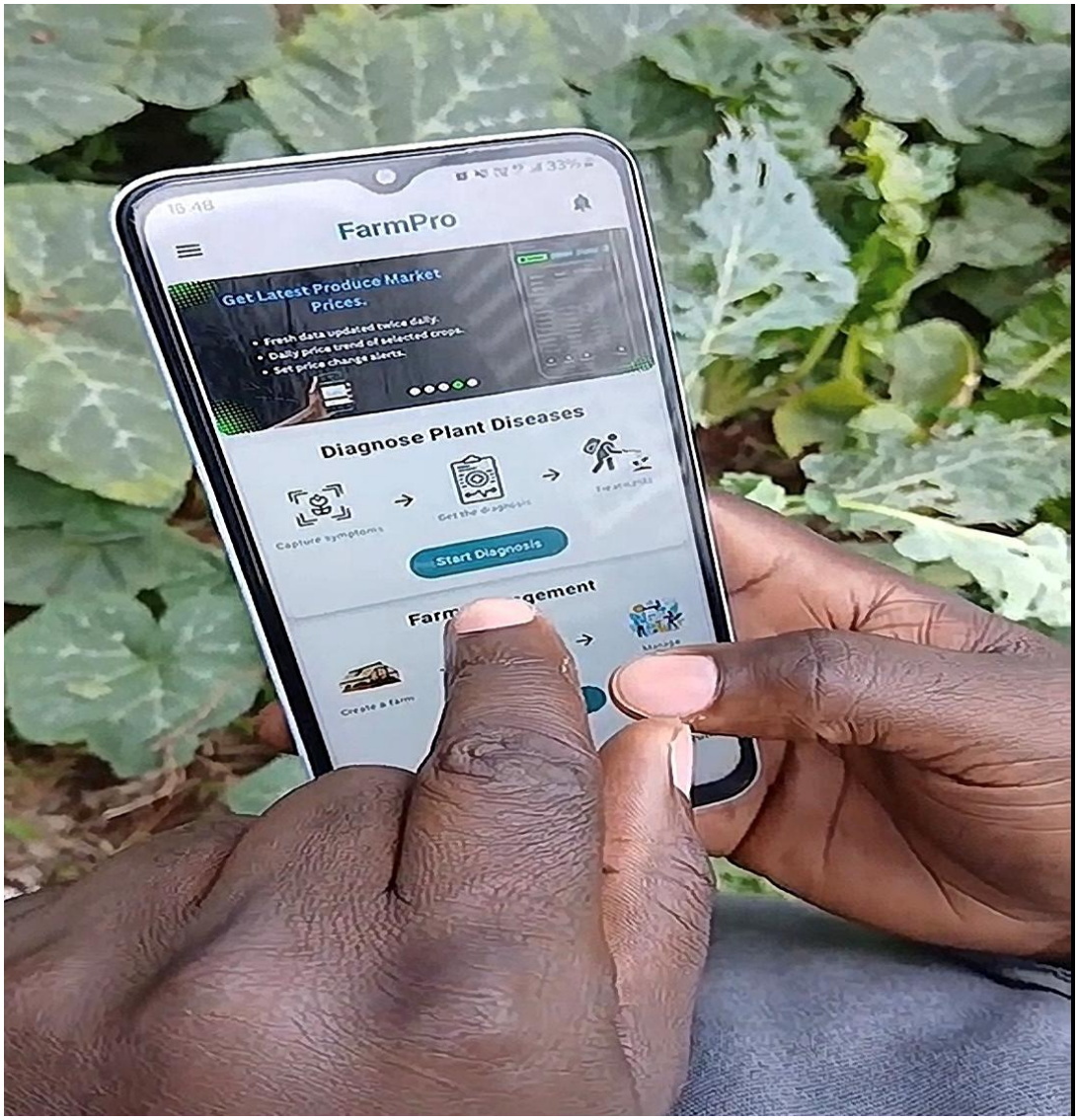


Plate 4.3: Farmer showing a pest and disease diagnosis application

Verbatim quotation (Focus Group Discussion):

> *"I use the Farmpro application to detect the crop diseases instantly using my phone."* (Smallholder farmer, FGD 1, male, age 47)

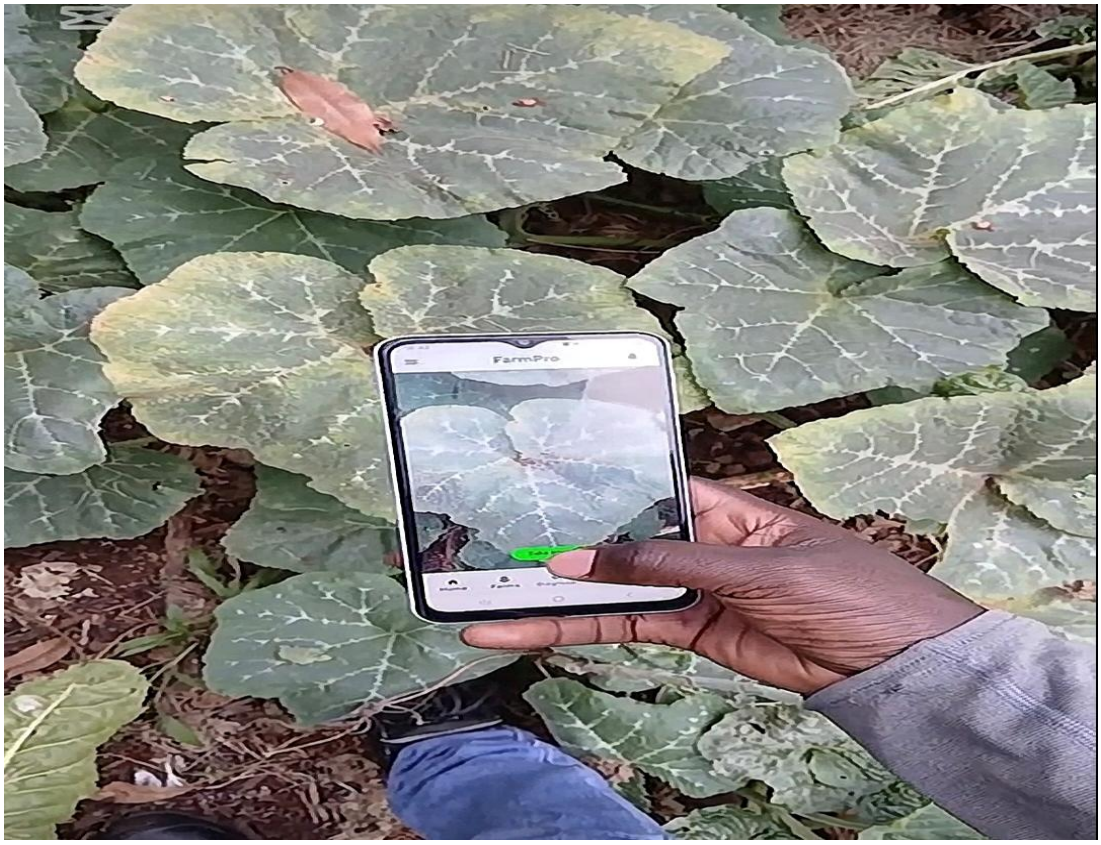


Plate 4.4: Farmer examining a field using the application

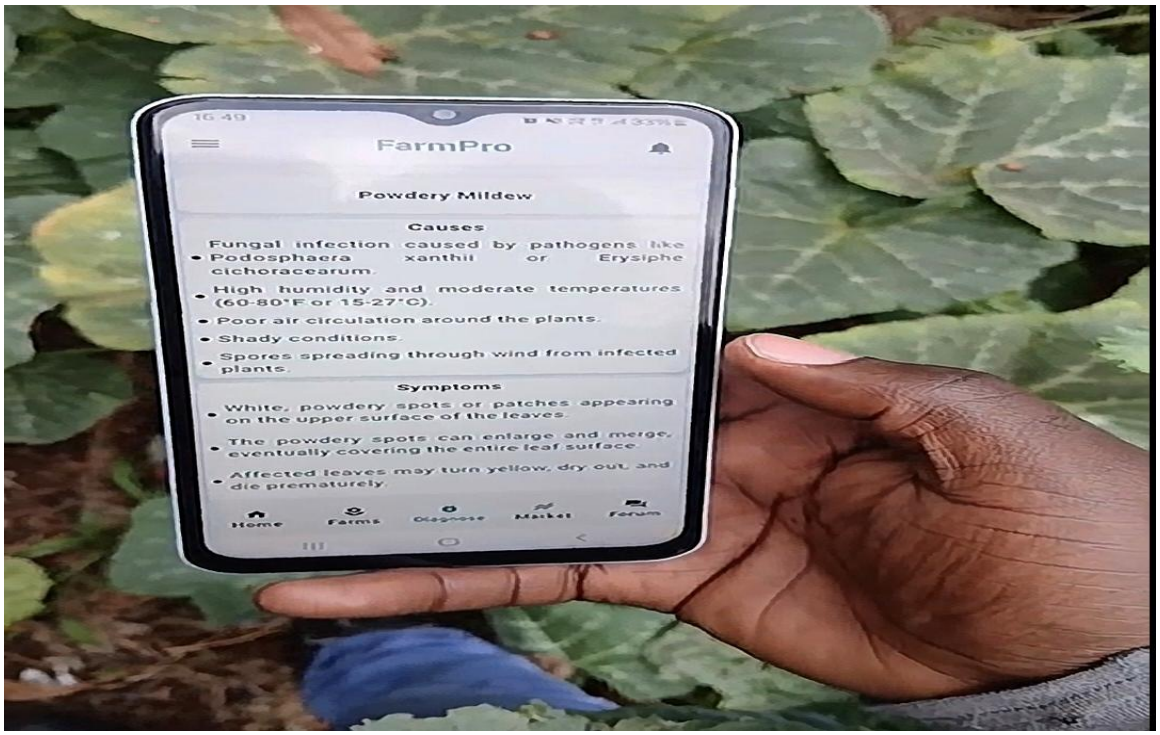


Plate 4. 5: Farmer showing the results produced by the app.

4.5: Farmers' willingness to adopt AI further

Farmers' Willingness to Try Artificial Intelligence Technologies

Overall attitudes toward the adoption of Artificial Intelligence (AI) in the agriculture are found to be predominantly positive. 72% of the respondents said they are willing to adopt if AI technologies are available and at a relatively reasonable price while another 20% would be willing to adopt if they are convenient and their benefits outweigh any negatives. 8% of the respondents however are not willing to adopt due to reasons such as complexity, expense and uncertainty.

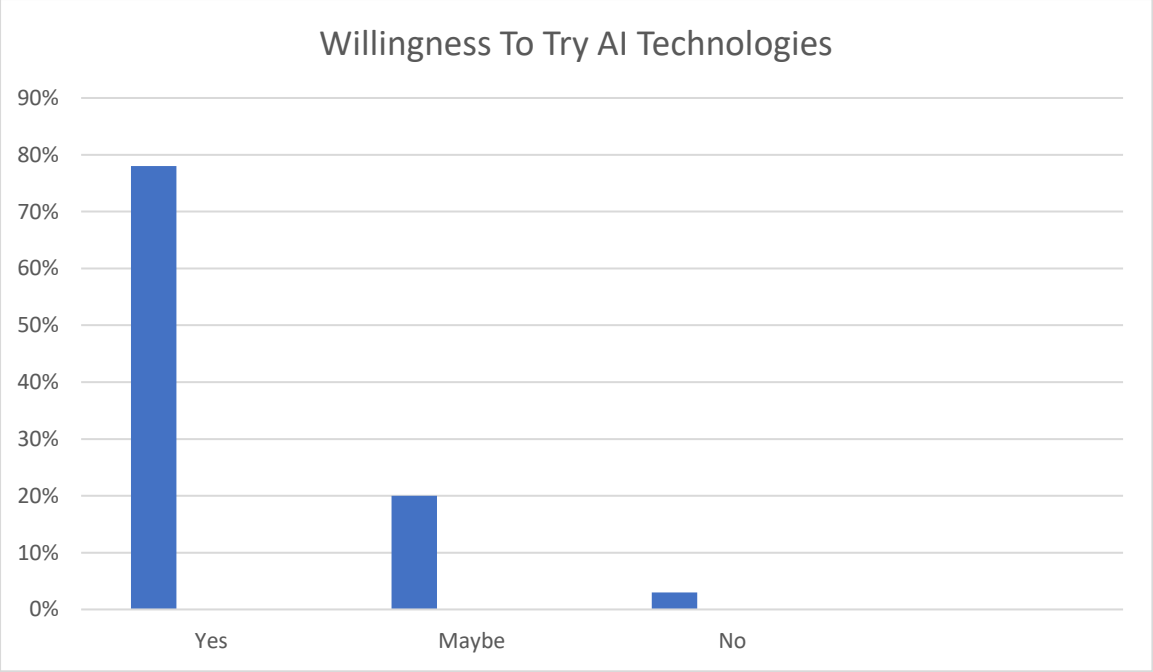


Figure 4.7: Willingness to adopt AI in the future (Source: Primary Data)

This shows there is great potential to adopt AI by farmers if there is proper training, support and to illustrate the benefits of the technology.

Most Desired AI Applications

These indicate that farmers value those technologies that tackle directly with production risks and provide information on decision-making processes over cropping and farming methods, weather pattern and market access.

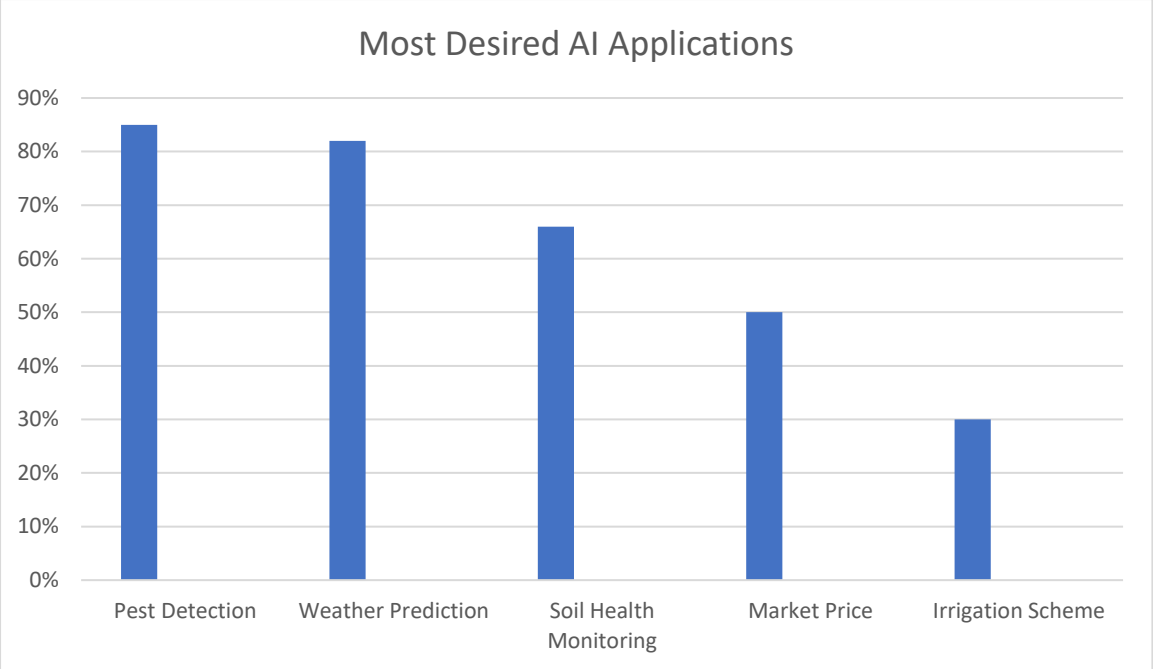


Figure4. 8: Most Desired AI Applications among Farmers (Source: FGDs).

Interpretation: This implies that the farmers evaluate technologies on direct treatment to production risk and improvement of decision-making for crops, weather, and market.

Farmers' Willingness to Pay for AI Services

The farmers' willingness to pay for AI supported agricultural services was also evaluated. It was found that 36% of the farmers were ready to pay a modest amount for AI service because they saw the advantages. Another 28% would pay for the service only if these technologies proved successful through demonstrations or the experience of other farmers. At the same time, 36% of the farmers were not willing to pay because of the money issues and lack of assurance of payback.

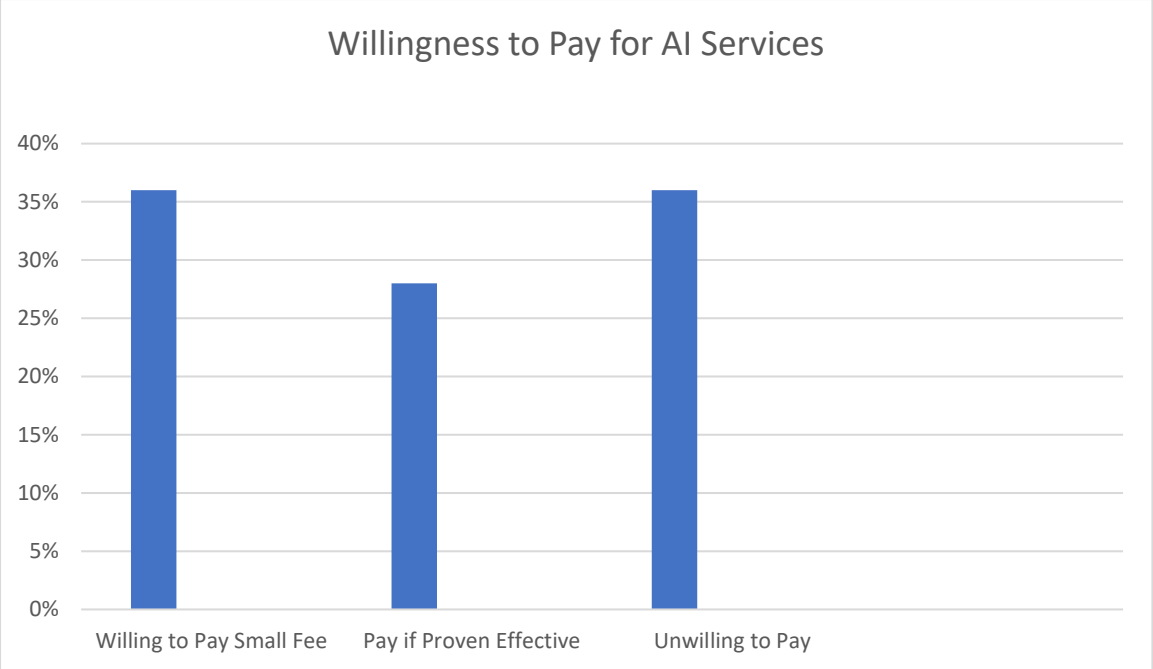


Figure 4.9: Farmers' Willingness to pay AI Services (Source: FGDs).

Interpretation: The above implies that although there is a very high potential for adopting AI there is a limitation posed by the price of AI applications. Demonstration projects, pilots and subsidized access to AI applications can therefore be the key factors that could promote AI adoption among Makonde District's farmers.

Description of pattern: The overall level of AI adoption is low but nearly all farmers are ready to embrace it if the above conditions are satisfied. The most pressing demands are pest detection and a good weather forecast. One-third of farmers would accept a minimal cost; another third would only use a free, subsidised, or established service. Trust depends on demonstrating results on neighbours' farms and getting help from extension agents.

Verbatim quotation (Interview):

> *"If I am being shown how to do it, and the AI can prevent the fall armyworm from ruining my maize, I'll be using it. I just have to be shown, though, and it'll have to be free. I'm not going to pay for what I don't understand. Let me try it for a season, without paying, and if my yield goes up, then I'll believe you."* (Farmer 6, smallholder, age 44).



Plate 4.6: Focus group discussion session with smallholder farmers in Chinhoyi.

A focus group discussion session with smallholder farmers in Chinhoyi, facilitated by the researcher. Participants shared their perceptions, concerns, and expectations regarding AI technologies for agriculture.

4.6 Discussion of results

Here, the results obtained are compared to the corresponding objectives of this investigation, examined in light of available literature, justified in observed trends and explained where discrepancies exist.

Farmers' knowledge of AI applications

Farmers in Chinhoyi exhibit both low and increasing awareness about the use of AI in agriculture. In the current study mobile weather forecasts were the most prevalent tools and extension officers were identified as currently underutilized sources of information. These trends are in line with Sithole and Olorunfemi (2024) who found that, despite there being very low levels of digital literacy in the case of smallholder farmers in SSA, awareness is created through informal peer groups rather than through the official extension system. The poor penetration of extension officers in this current study is also consistent with Manzeke Kangara et al. (2024) who stated that poor training of extension agents prevents efficient diffusion of climate smart and digital technologies in Zimbabwe. Two factors may explain the observed trend: firstly, the relatively new nature of the AI application means that digital agriculture is not integrated in extension systems; secondly the relatively high cost of data and smart phones hinders farmers from having directly interaction with most AI tools, leaving radio as the most dominant channel for accessing information. No contrary results came out in literature, apart

from in Kenya, where higher levels of AI adoption were found to have stemmed from the privately-led marketing efforts of agri-tech companies (Begho, 2025). The discrepancies may arise from the constrained telecommunication systems in Zimbabwe and low investment from the private sector in AI applications for agriculture.

Farmers' level of adoption of AI in current practices

This study shows the extremely low rate (12%) and the concentration on only commercial farmers of advanced AI use, although there is moderate use of basic digital tools (64%), on which future adoption can be based. Barriers of lack of training, high cost and bad internet are identified as the major issues preventing uptake. Ndlovu et al. (2024) showed a very similar adoption level and a strong digital divide for smart agriculture in Zimbabwe, also seeing only the commercial farmers using the technology. Similarly, Tashu et al. (2025) showed lack of data costs and network coverage as the most reported barriers to digital adoption in rural Zimbabwe. This shows it is interesting that lack of trust, rather than being the prime barrier, is only a secondary reason for adoption failure here; this may be due to commercial farmers having already benefited from using a variety of basic digital tools that work, such as weather apps and mobile money. Only 40% of non-adopters used this as a reason for their lack of adoption. In other African regions, such as Nigeria, trust was cited as the number one barrier to adopting technology (Etim, 2026); the difference can be explained as here the farmers already use certain technology in their everyday lives and know that they work, but are wary of using something that they are unsure how to use properly and that isn't as clearly provable as working as something else, compared to the previously untrusted systems that farmers may now be wary of. A self-critique here also comes with a concern about definition; some respondents may consider rule-based weather applications as 'AI', whereas a more advanced definition of AI would probably exclude these. Future work should make the distinction between narrow and general AI clearer.

Farmers' willingness to adopt AI further

Seventy two percent of farmers expressed willingness to adopt AI, with high willingness in pest identification and weather forecasting tools, but dependent on low cost, training, and peer demonstrations. This high degree of willingness contradicts very low actual adoption rates, but is congruent with the Technology Acceptance Model (TAM), wherein high perceived usefulness and very low perceived ease of use prevail (Davis, in theoretical framework). Similarly, Oliveira and Silva (2023) found Brazilian smallholders to be highly willing to adapt

yield improving technologies when supported by subsidies and trials to mitigate risk, contrasting with Dimitris' (2026) claim that farmers in developing countries have 'inertia towards adopting new technologies' as they are risk averse. However, sampling can explain this difference; while Dimitris surveyed farmers lacking previous exposure to any digital technology, this study's sample consists of farmers who already use some basic mobile application, thus increasing their willingness to adopt similar new technologies. The greatest tool requested, pest identification, is strongly influenced by fall armyworm outbreaks which are prevalent in Makonde District (Mugiyo, 2024). The conditions of adoption (free trials, training, and peer demonstrations) are supported by Roger's diffusion of innovations where observability and trialability play a role in adoption within the late majority group.

Consolidation of discussion

It can be seen from these three objectives that there is a similar trend: It is not that farmers in Chinhoyi are unwilling to adopt AI technology. Instead, they cannot due to several structural limitations (knowledge gaps, infrastructure deficiencies, and price restrictions). Low adoption thus becomes a reflection of high latent willingness. A few farmers who are already using AI as a commercial means can act as an "innovation hub" to disseminate it to others with efficient extension services and demonstration plots. Pest detection tool seems to have great appeal. It could be a viable pilot intervention area. Intervention studies to assess the real-field use and adoption over time with subsidized AI tools should be planned.

4.7 Chapter summary

This chapter showed the thematic analysis of the data gathered from the 30 farmers and extension officers of Chinhoyi. These findings include: (1) awareness level of AI is low and developing, weather apps have the highest awareness and extension agents are not adequately utilised; (2) the adoption rate of advanced AI is very low at 12%, moderate digital tool adoption at 64%, and the main reasons for not adopting these technologies are lack of training, cost, and poor network infrastructure; and (3) willingness to adopt is high at 72% and interest levels are highest in pest detection and weather forecast, depending on the affordability of these technologies, their ease of use, training and demonstration to farmers. The discussion reinforced these findings with studies already done in other areas of digital agriculture in SSA, and confirmed that, in Chinhoyi, trust is not as a critical barrier to AI adoption. Chapter 5 covers the conclusions and recommendations.

CHAPTER 5: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This last chapter is a summary of the entire research. It summarises the problem investigated, the research procedure, the constraints encountered during the study and the major findings of the study presented in Chapter 4. Taking the study findings as a guide, the chapter makes research-based recommendations to the policy makers, extension services, as well as further research. The recommendations aim at enhancing AI technology adoption by farmers in Chinhoyi.

5.2 Summary of Findings

The aim of the study was to identify the perceptions of farmers toward the application of AI technology for the optimisation of agriculture in Chinhoyi, Zimbabwe. This research was motivated by the global move towards Agriculture 4.0 and the continually existing digital divide, which could leave smallholder farmers in rural Zimbabwe lagging behind with AI offering potential to increase productivity, resource efficiency, and climate resilience. The study employed a qualitative descriptive case study design to have an in depth investigation into the farmers' perceptions in their real-world setting. The sample size was thirty consisting of 22 smallholder farmers, 5 commercial farmers and 3 agricultural extension officers; this sample was selected using purposive sampling from Chinhoyi. The instruments that were used for data collection were semi structured interviews, focus group discussions and observations. Analysis was conducted using thematic analysis according to the six-phase framework proposed by Braun and Clarke. These analyses produced themes based on three research objectives:

Some limitations to the study were evident. First, focusing only on one district does not allow generalization of the results to other areas having different agricultural systems or infrastructure. Second, there is potential for social desirability bias in self-reported data whereby participants might have given answers that they perceived were socially desirable rather than their true opinion. Third, being cross sectional the study observed opinions at only one point in time and thus could not capture how farmers' attitudes may change as their experience of AI grew. Fourth, there were some difficulties related to language barriers and the

need for translation since there are no specific words for some of the AI technologies. Fifth, it was not possible to get to some farms due to the presence of heavy rains, hence excluding some voices. Finally, smallholder farmers have low existing AI knowledge, and consequently some farmers' answers could have been speculative rather than experiential. Despite all the limiting factors meaningful inferences were made and the following conclusions drawn.

5.3 Conclusions

The findings are reported in a research context. The results below are taken directly from the data described in Chapter Four, giving summaries to the three sub-problems in Chapter One.

From the study, the researchers found that the farmers in Chinhoyi generally had a low but increasing awareness of the role of AI in agriculture. Farmers that claimed that they had heard of the term Artificial Intelligence represented 80%, however this term was very vague to them or often confused with the use of general digital technologies. The AI adjacent tool that was best known to farmers, 72%, was mobile based weather forecasting. Radio, TV were significant sources of AI awareness to the farmers (76%), followed by friends/neighbours (56%) and extension officers were reported by 36% of farmers. This suggested that there was underuse of extension officers as a means of disseminating digital agricultural information. The researcher found that gaps in digital literacy and lack of local language applications had restricted higher awareness.

Equally important, the analysis found very low uptake of advanced AI at a low 12% (all are commercial farmers and use actual AI based technologies such as drone based crop monitoring or AI enabled pest detection apps) but adoption of basic digital technologies are at a medium level at 64% (usage of weather mobile apps, WhatsApp based farming groups and basic soil testing). This indicates that whereas farmers are not using sophisticated AI technologies at present, simple digital technologies are adopted and these could form building blocks towards their eventual usage of AI technologies. The main obstacles to adoption identified are training and awareness (reported by 88% non-adopters), cost of devices and data (72%), limited internet connectivity (60%) and low trust in technology (40%). This last barrier (trust) appeared as a secondary obstacle and thus it seems that technology related constraints (cost and connectivity) are more pressing.

Moving on, the results indicate a high acceptance of AI technology with 72% of farmers expressing definitely willing to try AI technologies while another 20% of respondents indicated they are willing to try; this collectively is 92% of farmers. The specific functions where AI is

requested by the willing farmers include pest and disease detection (87%) followed by accurate prediction of weather services (83%) a scenario which reflects the existing real-world threats on farmers lives through fall armyworm and weather inconsistency (rain in Chinhoyi). 36% are willing to pay a low amount for the AI technology, 28% of respondents are willing to pay only if proven effective and the final 36% of farmers indicated that they are not willing to pay as they prefer it to be free or subsidised. Trust of recommendations by AI is reliant on three variables: if they see it on their neighbours' farm, if trained by extension personnel of their trust, and a free trial. This study, therefore, concludes that poor adoption of AI is due to inaccessibility of technology rather than its perceived futility or the farmer's unreadiness.

5.4 Recommendations

In light of the aforementioned findings, the following policy recommendations are proposed to policymakers, extension service agents, development practitioners, and other researchers.ARDAS should aim to train and impart knowledge to all extension workers in Chinhoyi on the use of AI and tailor training accordingly. This will help in providing relevant advice to farmers on the use of AI.Moreso, it is recommended that extension officers are given tools, such as a tablet pre loaded with useful applications, to aid them to demonstrate the working of AI during on-site farmer visits. Tools such as offline weather, disease or pest diagnostic applications are examples. The use of live demonstrations could help to break the identified barrier to trust. Farmer to farmer learning groups should be established where progressive commercial farmers educate the other smallholders around them. This strategy could be very useful since the study found that 56% of farmers gain knowledge through other farmers.

The government is encouraged to offer AI-based pest detection and weather forecast services, with subsidised payment scheme or vouchers, for smallholder farmers. In light of the fact that 36% of the farmers cannot pay anything, initially, the services can be offered at either free of cost or minimum cost through a public-private partnership. Infrastructural development-mobile network penetration, as well as the setting up of charging stations powered by solar in rural areas, is an essential investment if AI adoption is to be realised. Ministry of ICT should pilot the extension of rural connectivity to Chinhoyi. In terms of localisation policies, AI farming solutions should be designed and available in Shona language and other vernacular languages with user friendly, pictorial interfaces suitable for low literate farmers.

REFERENCES

Abdelmoneim, H. M., Alhudhaibi, A. M., Taha, R. H., Bendif, H., & Taha, T. H. (2026). Integrating resistance biology, virulence networks, and precision therapeutics against multidrug-resistant Pseudomonas aeruginosa. *Infection*, 1-22.

Aijaz, N., Lan, H., Raza, T., Yaqub, M., Iqbal, R., & Pathan, M. S. (2025). Artificial intelligence in agriculture: Advancing crop productivity and sustainability. *Journal of Agriculture and Food Research*, *20*, 101762.

Baxter, P., & Jack, S. (2008). Qualitative case study methodology: Study design and implementation for novice researchers. *The qualitative report*, *13*(4), 544-559.

Begho, T., Daubry, T. P., & Irabor, A. E. (2025). A Scoping Review of Artificial Intelligence and the Future of African Agriculture: Opportunities, Challenges and the Path Forward. *Advances in Agriculture*, *2025*(1), 2862074.

Chidoko, C., Jimu, T., & Ndhlovu, E. (2026). Food Imports and the Growing Debt Burden in Sub-Saharan Africa. In *Agriculture and Sustainable Development in Sub-Saharan Africa: Resilience and Recovery Toward Sustainable Futures* (pp. 181-193). Cham: Springer Nature Switzerland.

Costa, F., Frecassetti, S., Rossini, M., & Portioli-Staudacher, A. (2023). Industry 4.0 digital technologies enhancing sustainability: applications and barriers from the agricultural industry in an emerging economy. *Journal of Cleaner Production*, *408*, 137208

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Dahlin, E. (2019). Are robots stealing our jobs?. *Socius*, *5*, 2378023119846249.

Devika, P., Anushobini, S., & Harini, V. Smart AgriSense: AI-Powered Hybrid System for Crop Health Monitoring. *Proceedings Copyright*, *309*, 315.

Dimitris, P., Roido, M., Petros, K., & Olga-Eleni, A. (2025). The Use of New Technologies in the Primary Production Sector. *Strategic Planning for Energy and the Environment*, 727-754.

Dube, S., & Manik, S. (2025). A Literature Review on Climate Smart Strategies: Localising Climate Action and Advancing Some Possibilities for Artificial Intelligence in Resilience Building for Small-Scale Farmers in Zimbabwe. *Geo: Geography and Environment*, *12*(2), e70038.

Fundira, T., Nyangoni, E. B., Munyati, D., Rukwishuro, T., Gumunyu, E., & Muwiri, A. Z. (2024, November). Adoption, barriers, and scaling opportunities of artificial intelligence and Internet of Things in the Zimbabwean Food Manufacturing Industry. In *2024 3rd Zimbabwe Conference of Information and Communication Technologies (ZCICT)* (pp. 1-7). IEEE.

GAMBELLI, G. (2024). THE ROLE OF ARTIFICIAL INTELLIGENCE IN INTERNATIONAL NEGOTIATION.

Hirose, M., & Creswell, J. W. (2023). Applying core quality criteria of mixed methods research to an empirical study. *Journal of Mixed Methods Research*, *17*(1), 12-28.

Javaid, M., Haleem, A., & Singh, R. P. (2023). A study on ChatGPT for Industry 4.0: Background, potentials, challenges, and eventualities. *Journal of Economy and Technology*, *1*, 127-143.

Johnson, G. U., Towell-Barnard, A., McLean, C., Robert, G., & Ewens, B. (2025). Methodological Insights From Evaluating a Family Member's Voice Reorientation Programme: An Interpretive Descriptive Approach. *Nursing open*, *12*(9), e70291.

Johnson, G. U., Towell-Barnard, A., McLean, C., Robert, G., & Ewens, B. (2025). Methodological Insights From Evaluating a Family Member's Voice Reorientation Programme: An Interpretive Descriptive Approach. *Nursing open*, *12*(9), e70291.

KAKIZ, H. The Future of Sustainable Labor Markets (2026–2030): Emerging Occupations in the Age of Artificial Intelligence.

Kaminski, J. (2011). Diffusion of innovation theory. *Canadian Journal of Nursing Informatics*, *6*(2), 1-6.

Khan, N., Ray, R. L., Kassem, H. S., Hussain, S., Zhang, S., Khayyam, M., ... & Asongu, S. A. (2021). Potential role of technology innovation in transformation of sustainable food systems: A review. *Agriculture*, *11*(10), 984.

Kim, D. K., Ochar, K., Iwar, K., Ha, B. K., & Kim, S. H. (2025). Cowpea (Vigna unguiculata L.) production, genetic resources and strategic breeding priorities for sustainable food security: A review. *Frontiers in plant science*, *16*, 1562142.

Klingwort, J., Leach, N. M., & Burger, J. (2026). Performance of models for monitoring sustainable development goals from remote sensing: A three-level meta-regression. *arXiv preprint arXiv: 2601.06178*.

Kumari, K., Mirzakhani Nafchi, A., Mirzaee, S., & Abdalla, A. (2025). AI-driven future farming: achieving climate-smart and sustainable agriculture. *AgriEngineering*, *7*(3), 89.

Lokonon, B. E., Houetohossou, S. C. A., Tchede, B. A., Yapi, R. B., Cailleau, A., Haydon, D. T., & Bonfoh, B. (2026). The use of artificial intelligence based modelling techniques in One Health-related infectious disease studies in Sub-Saharan Africa: a review. *Frontiers in Artificial Intelligence*, *9*, 1778800.

Manono, B. O., Mwami, B., Mutavi, S., & Nzilu, F. (2026). Precision farming with smart sensors: Current state, challenges and future outlook. *Sensors*, *26*(3), 882.

Manzeke-Kangara, M. G., Muwaniki, C., Siziba, S., Chamboko, T., Mtambanengwe, F., & Wedekind, V. (2024). Evolution of agricultural extension in Zimbabwe: emerging technologies, training needs and future possibilities. *South African Journal of Agricultural Extension*, *52*(2), 21-55.

Martin, A., & Grudziecki, J. (2006). DigEuLit: Concepts and tools for digital literacy development. *Innovation in teaching and learning in information and computer sciences*, *5*(4), 249-267.

Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., & Oak, S. (2025). Artificial intelligence index report 2025. *arXiv preprint arXiv:2504.07139*.

Meijer, S. S., Catacutan, D., Ajayi, O. C., Sileshi, G. W., & Nieuwenhuis, M. (2015). The role of knowledge, attitudes and perceptions in the uptake of agricultural and agroforestry innovations among smallholder farmers in sub-Saharan Africa. *International journal of agricultural sustainability*, *13*(1), 40-54.

Mensah, P., Ayidzoe, M., Bawah, F., Bediako, E., & Ozor, N. (2024). Promoting digital literacy among farmers: unlocking the potential of artificial intelligence enabled crop pests/disease detection mobile application.

Mhaka, S., & Runganga, R. (2023). Impact of agricultural production on economic growth in Zimbabwe. *Managing Global Transitions*, *21*(4).

Mugiyo, H. (2024). Diagnostic study of the maize-based farming system in South and East Africa: pathways to sustainable intensification and diversification-a case study of Makonde, Masvingo and Murehwa districts in Zimbabwe.

Mustonen-Ollila, E., & Lyytinen, K. (2003). Why organizations adopt information system process innovations: a longitudinal study using Diffusion of Innovation theory. *Information Systems Journal*, *13*(3), 275-297.

Muzanenhamo, T. J., MUBAYA, C., & Tsvere, M. (2025). Adopter Category Characterizations and the Adoption of Mobile Phone Applications for Improved Small-scale Commercial Agriculture in Chitomborwizi-Makonde District, Zimbabwe. *EAST AFRICAN JOURNAL OF AGRICULTURE AND BIOTECHNOLOGY Учредители: East African Nature and Science Organization*, *8*(1), 60-77.

Ndlovu, B., Dube, S., Maguraushe, K., & Dube, S. P. (2024, July). Factors Influencing the Adoption of Artificial Intelligence in Smart Agriculture. In *Proceedings of the International Conference on Industrial Engineering and Operations Management*.

Ojo, T. A. (2024). Botswana and South Africa's Response. *African Women in the Fourth Industrial Revolution: Change, Policies, and Approaches*.

Oliveira, R. C. D., & Silva, R. D. D. S. E. (2023). Artificial intelligence in agriculture: benefits, challenges, and trends. *Applied Sciences*, *13*(13), 7405.

Park, Y. J., Jeong, Y. J., An, Y. S., & Ahn, J. K. (2022). Analyzing the factors influencing the intention to adopt autonomous ships using the TOE framework and DOI theory. *한국항해항만학회지*, *46*(2), 134-144.

Ramat, G., Santi, E., Paloscia, S., Fontanelli, G., Pettinato, S., Santurri, L., ... & Lili Chabaane, Z. (2023). Remote sensing techniques for water management and climate change

monitoring in drought areas: case studies in Egypt and Tunisia. *European Journal of Remote Sensing*, *56*(1), 2157335.

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In *An integrated approach to communication theory and research* (pp. 432-448). Routledge.

Saldaña, J. (2021). The coding manual for qualitative researchers.

Sarun, H., Rotana, S., & Chhunla, C. (2026). The Importance of Artificial Intelligence in Enhancing Sustainable and Climate-Resilient Agriculture in Cambodia: A Narrative Review. *Journal of Agriculture and Environment*, *3*(1), 124-132.

Sarvestani, A. A. (2026). Ethics-Centered Approach to the Development and Application of Artificial Intelligence in Agriculture.

Silva, F. T. D., Baierle, I. C., Correa, R. G. D. F., Sellitto, M. A., Peres, F. A. P., & Kipper, L. M. (2023). Open innovation in agribusiness: Barriers and challenges in the transition to agriculture 4.0. *Sustainability*, *15*(11), 8562.

Sithole, A., & Olorunfemi, O. D. (2024). Sustainable agricultural practices in Sub-Saharan Africa: a review of adoption trends, impacts, and challenges among smallholder farmers. *Sustainability*, *16*(22), 9766.

Tarek, A., Abdelhadi, A., & Karachiwalla, N. (2025). Digital agricultural technology in Egypt: Insights from app developers.

Tarusarira, J., & Maviza, G. (2025). Climate, security, and the study of religion in Africa: Insights from Northern Mozambique. *Utambuzi: Journal for the Study of the Religions of Africa and its Diaspora*, *8*(1), 82-93.

Tashu, K. T., Moyo, T., & Marumahoko, S. (2025). Emerging Technologies and the Agrarian Sector in Zimbabwe: Prospects and Challenges. *Zimbabwe Journal of Business, Economics and Management*, *4*(1).

Yin, R. K. (2018). *Case study research and applications* (Vol. 6). Thousand Oaks, CA: Sage.

APPENDICES

Appendix 1: Semi-Structured Interview Guide for farmers.

Title: Farmers' Perceptions on the Adoption of Artificial Intelligence for Optimising Agriculture in Chinhoyi, Zimbabwe

Thank you so much for taking time out of your busy schedule to meet with me today. My name is Vanessa Mageva. I am a student from Bindura University of Science Education and I am conducting a research study for my dissertation. As a farmer here in Chinhoyi, your experience and insights are valuable and I am very eager to learn from your perspective. The purpose of this study is to understand your thoughts, experiences and views on using modern digital technologies specifically Artificial Intelligence(AI) to improve and optimize farming practices. There are no right or wrong answers today. I am simply here to understand your personal opinions and challenges you face and what you think about the future of these technologies in our local community. Your responses will be kept strictly confidential and used for academic purposes only.

SECTION A: FARMERS BACKGROUND

1. How long have you been farming in Chinhoyi?

2. What is the size of your farm and what are your main crops?

SECTION B: OBJECTIVE 1-FARMERS KNOWLEDGE OF AI APPLICATIONS IN AGRICULTURE.

3. Have you ever heard the term Artificial Intelligence or AI in farming?

4. If yes to question 3 above, what do you understand by the term Artificial Intelligence (AI) in agriculture?

5. Can you describe any farming tools or practices you know that use AI?

6. Which sources have helped you learn about AI technologies used in farming?

SECTION C: OBJECTICE 2-FARMERS' LEVEL OF ADOPTION OF AI IN CURRENT PRACTICES.

7. Are you using any AI-related technologies on your farm?

8. If yes to 3 above, explain how they are being used?

9. For the tools you use:

a) How did you learn to use them?

b) Have they changed your farming decisions?

c) Have they improved your yields or reduced your costs?

10. If you are not using AI now, what are the main reasons?

11. What benefits do you think AI technologies can bring to farmers in Chinhoyi?

12. What challenges or barriers do farmers face in adopting AI technologies?

13. How affordable and accessible do you think AI technologies are for small-scale farmers?

SECTION D: OBJECTIVE 3-FARMERS WILLINGNESS TO ADOPT AI FURTHER.

14. Would you be willing to try an AI tool for your farm?

15. If no to question 14 above, what are your reasons?

16. Would you be willing to pay for an AI service monthly or per season?

17. If no to question 16 above, what are your reasons?

18. What would make you trust AI recommendations more?

19. What support would you need to use AI on your farm more?

20. What recommendations would you give to improve the adoption of AI technologies among farmers in Chinhoyi?

Thank you very much for taking the time to share your experiences and insights with me. Your contribution is valuable to this research.

Appendix 2: Focus Group Discussion Protocol

Project Title: Farmers' perceptions on the adoption of Artificial Intelligence for optimising agriculture in Chinhoyi, Zimbabwe.

Hello everyone, and welcome. Thank you all so much for taking the time to join this discussion today. My name is Vanessa Mageva. I am a student from Bindura University of Science Education and I am carrying out research for my dissertation on your perceptions on the adoption of AI for optimising agriculture. I am not here to sell any technologies and I do not work for any tech company. The goal of this group is to listen to your honest thoughts, your concerns, your excitements or your doubts about these tools. There are no right or wrong answers today, differing opinions are highly welcome. Your responses will be kept strictly confidential and used for academic purposes only.

Facilitation Notes:

- **Ensure participants are comfortable and discussions are culturally appropriate.**
- **Encourage equal participation and avoid dominance by a few voices.**
- **Record key themes and consensus points.**

1. What comes to your mind when you hear the term Artificial Intelligence (AI) in agriculture?

2. What types of AI technologies or smart farming tools are farmers in this area aware of?

3. Which AI technologies are currently being used by farmers in Chinhoyi?

4. How useful do you think AI technologies are in improving farming activities and agricultural productivity?

5. What benefits have farmers experienced or expect to experience from using AI in agriculture?

6. What challenges discourage farmers from adopting AI technologies?

7. How does the level of education or training affect farmers' adoption of AI technologies?

8. What role do government agencies, agricultural extension officers, or organisation's play in promoting AI adoption among farmers?

9. Are farmers in Chinhoyi willing to adopt more AI technologies in the future? Why or why not?

10. What suggestions or recommendations would you give to improve the adoption of AI technologies among farmers in Chinhoyi?

Thank you very much for taking the time to share your experiences and insights with me. Your contribution is valuable to this research.

Appendix 3: Field Observation Checklist

Project Title: Farmers' perceptions on the adoption of Artificial Intelligence for optimising agriculture in Chinhoyi, Zimbabwe.

Purpose: To enable the researcher to directly observe and record the presence, usage, and condition of Artificial Intelligence (AI) technologies and related farming practices among farmers

NUMBER	OBSERVATION ITEM	YES/NO
1	Presence of smartphones or digital devices used for farming activities	
2	Use of mobile farming applications or digital agricultural platform	
3	Availability of internet connectivity/network access on the farm	
4	Presence of smart irrigation systems or automated watering system	
5	Use of weather forecasting applications or digital weather information Presence or use of drones for crop monitoring or spraying	
7	Evidence of digital record keeping for farming activities	
8	Use of AI-supported pest or disease detection methods	
9	Availability of electricity or solar power supporting AI technologies	

10	Farmers demonstrating knowledge or skills in using AI technologies	

Appendix 4: Bindura University Research Approval Letter.

Bindura University of Science Education

SUSTAINABLE DEVELOPMENT DEPARTMENT

BINDURA,ZIMBABWE
WhatsApp : +263773281212
E-mail: jbowora@buse.ac.zw or jb.bowora@gmail.com

BINDURA UNIVERSITY OF SCIENCE EDUCATION

CHAIRPERSON'S OFFICE

Friday, 17 October 2025

TO WHOM IT MAY CONCERN

Dear Sir/Madam

RE: RESEARCH SUPPORT LETTER FOR SUSTAINABLE DEVELOPMENT STUDENT

This is to confirm that **MAGEVA VANESSA** Registration Number **B223991B** is our fourth-year student doing Bachelor of Science (Honours) Degree in Development Studies (HBSc.DG) at Bindura University of Science Education in the Sustainable Development Department.

In the fourth-year, students are required to do field research which require them to do data collection for their research purposes from various sources as part of their degree programme.

Kindly accord him/her the due cooperation the student truly deserves.

Yours faithfully,

CHAIRMAN
GEOGRAPHY DEPARTMENT
FACULTY OF SCIENCE

Dr. J. Bowora (PhD)
(Chairperson)