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Determinants of food security among cereal farmers in Homa Bay County, Kenya.

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DETERMINANTS OF FOOD SECURITY AMONG CEREAL FARMERS IN HOMA BAY COUNTY, KENYA

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A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF MANAGEMENT IN AGRIBUSINESS OF STRATHMORE UNIVERSITY

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Dissertation contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Approval

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ABSTRACT

Food insecurity remains a persistent challenge in developing nations, particularly in Kenya, where over half of the population faces moderate to severe cases. Despite numerous national strategies, progress toward achieving Sustainable Development Goal 2 on Zero Hunger remains limited. Homa Bay County is among the regions most affected by food insecurity, with nearly half of its population considered food insecure. While several studies have examined the determinants of food security in Kenya, limited empirical evidence exists on the influence of agricultural mechanization, digital agricultural information technologies (DAITs), and sustainable agricultural practices (SAPs) among cereal farmers. This study bridges that gap by assessing how these three technological and sustainable dimensions affect household food security in Homa Bay County. A mixed-methods research design was applied, integrating quantitative and qualitative approaches. Primary data were collected from 473 cereal farming households across Suba North, Karachuonyo, and Rangwe sub-counties using structured household surveys, 3 key informant interviews (KIIs), and 3 focus group discussions (FGDs). Quantitative data were analyzed using Propensity Score Matching (PSM), Ordered Logit, and Poisson regression models, while thematic analysis used on qualitative data to enrich interpretation. Findings presented that 76.1% of farmers had adopted some form of agricultural mechanization, mainly in land preparation, which significantly enhanced household food consumption scores. Mechanized farmers demonstrated higher food diversity, improved yields, and increased income levels compared to non-mechanized counterparts. Results also presented that adoption of DAITs had a positive and significant effect on food security, as digital tools improved farmers' access to agricultural information, markets, and weather forecasts, enhancing decision-making and resilience. Similarly, the adoption of at least three sustainable agricultural practices significantly improved dietary diversity and food availability, highlighting their role in promoting long-term agricultural resilience and nutritional adequacy. The study concludes that integrating mechanization, digital innovation, and sustainable agricultural practices forms a synergistic pathway toward achieving food security among farmers. Socioeconomic factors such as income, education, farming experience, and institutional support were enablers of technology adoption. The study recommends policies that promote affordable mechanization services, enhance digital infrastructure and literacy, strengthen extension systems, and incentivize sustainable farming adoption. It further advocates for inclusive rural financing, improved market access, and nutrition-sensitive agricultural interventions to foster resilience and reduce food insecurity.

Key words: *Food security, Agricultural mechanization, Agricultural technologies, Sustainable agricultural practices, Food Security*

DEDICATION

This Dissertation has been dedicated to my kids as well as my family as a cornerstone for academic excellence.

May this work be truthfully used to change lives and contributes to efforts to attain *ZERO HUNGER* around the World.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS AND ACRONYMS

A.M	- Agricultural Mechanization
CA	- Conservation Agriculture
FIES	- Food Insecurity Experience Scale
FAO	- Food and Agriculture Organization of United Nations
GIS	- Geographic Information systems
GPS	- Global Positioning System
HFIAS	- Household Food Insecurity Access Scale
HH	- Households
HDDs	- Households Dietary Diversity scores
FCS	- Food Consumption Score
IFAD	- International Finance for Agricultural Development
FIES	-Food Insecurity Experience Scale
IoT	- Internet of Things
KEPHIS	- Kenya Plant Health Inspectorate Service
IT	- Information and telecommunication technologies
KNBS	- Kenya National Bureau of Statistics
KALRO	- Kenya Agricultural and Livestock Research Organization
PPT	- Push Pull Technology
S.I	- Sustainable Intensification
UNICEF	- United Nations International Children Education Fund
WHO	- World Health Organization
WFP	- World Food Programme

DEFINITIONS OF TERMS

Key Terms	Definition	Source
Agricultural Information Technologies	Creative applications of information and communication technologies (ICT) in the agricultural sector that support increased farm income while enhancing the sustainable management of natural resources.	Kolawole (2019)
Agricultural Mechanization	It involves the utilization of various tools, machinery and farm implements, including basic and simple hand tools and advanced and motorized equipment.	FAO 2016
Food Consumption Score (FCS)	It is an indicator used to evaluate a household's diet quality and food security by examining the diversity, frequency, and nutritional value of foods consumed over the previous seven days. The measure applies weighted scores to different food groups such as staples, proteins, vegetables, and fruits based on their relative nutritional significance	FAO 2023
Household Dietary Diversity Score (HDDS)	It considers the variety of food groups consumed by a household over a specific period, typically 24 hours or 7 days. It indicates food security and nutritional adequacy, with higher scores reflecting greater dietary diversity and potential nutrient intake	FAO 2023
Food Insecurity Experience Scale (FIES)	It measures the range of different food groups eaten by a household within a defined reference period, usually the previous 24 hours or seven days. The indicator serves as a proxy for food security and the adequacy of nutrition, where higher values suggest more diverse diets and a greater likelihood of sufficient nutrient consumption.	FAO 2023
Food Security	It is when humanity, always maintains physical, economic and social access to adequate, nutritious, and safe, food that aligns with their dietary preferences and needs for a healthy and active life.	World Food summit 1974
Sustainable Agricultural Practices	The practices that improve agricultural productivity of agricultural ecosystems without negatively affecting their capabilities to produce food for the future generations and increase environmental conservation and adaptability to climate change	Researcher (2023)

CHAPTER ONE
INTRODUCTION

1.1 Introduction

This chapter outlines its background, introducing key variables, and presenting the problem statement. It also details the research specific objectives and questions that guided the study, along with its scope and significance. This was the foundation upon which this study established its relevance within the research area.

1.2 Background of the Study

Despite producing enough food globally, achieving *zero hunger* by 2030, as outlined in the SDGs, remains a significant challenge due to complex political, socio-economic, and environmental factors, leading to millions being undernourished (United Nations, 2018; World Vision International, 2021). United Nations refers food security as when all humans, always maintain physical, economic and social access to adequate, safe, and nutritious food that aligns with their dietary preferences and needs for an active and healthy life. However, nearly a billion people suffer from malnutrition globally, with approximately 16 percent residing in developing nations (United Nations Committee on World Food Security, 1974; FAO, 2022). Chronic hunger affects one in nine people globally, with developing countries particularly vulnerable, where around 12.9% of the entire population was considered undernourished in 2014, highlighting the persistent challenge of food insecurity (Klytchnikova et al., 2017).

Hunger is a growing global concern, with 11% of all people in the world suffering from nutritional deficiencies in 2017, and the population of undernourished individuals rising to 821 million by that year (FAO et al., 2018). Urbanization and population growth are causing rising food and nutrition insecurity, traditionally more prevalent in rural areas (Balineau, 2021). Despite hopes for improvement, the COVID-19 outbreak has increased food insecurity, with estimates indicating that about 702 to 828 million people globally were severely hit by hunger in 2021. This represents an increase of about 150 million since the pandemic begun, with approximately 2.3 billion individuals affected by moderate to severe food insecurity levels, posing a significant threat to global well-being (FAO, UNICEF, IFAD, WHO and WFP, 2022). Additionally, climate change creates a further risk to food production, potentially putting millions more at risk of hunger and poverty in the coming decades (Squires, 2020).

In addition, regional disparities continue to widen, with Sub-Saharan Africa experiencing some of the highest levels of food insecurity globally. Over a quarter of the population in Central and Eastern Africa faces food insecurity, with conditions steadily worsening since 2014 (FAO, 2024). This trend underscores the unequal distribution of food security gains and highlights the vulnerability of developing regions to global shocks such as pandemics, conflicts, and climate variability.

Kenya reflects these broader regional challenges. The country has been identified among food-insecure nations, with sluggish progress toward achieving both the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs) (Musyoka et al., 2020; FAO et al., 2022). Approximately 2.6 million Kenyans face food insecurity, with significant disparities across counties, particularly in arid and semi-arid regions and counties such as Homa Bay (KNBS, 2018). Furthermore, more than half of the population experiences moderate to severe food insecurity, emphasizing the urgency of addressing structural and systemic barriers to food access.

1.2.1 Food security

Food security is a multidimensional concept that is best understood through a funnel approach that moves from the global context to the household level where it is ultimately experienced and measured.

At the global level, food security has been under immense strain between 2015 and 2024, with projections indicating that approximately 600 million people could suffer from undernourishment by 2030 (FAO, 2020; Financial Times, 2024). Various factors have contributed to this growing crisis, including the COVID-19 pandemic, geopolitical conflicts such as the Russia–Ukraine war, climate-related disruptions, and limited adoption of agricultural inputs and technology. These challenges have resulted in a significant increase in hunger, with the number of undernourished individuals estimated to range between 713 and 757 million in recent years (FAO, 2020; Financial Times, 2024). The United Nations emphasizes that achieving zero hunger by 2030 will require substantial and coordinated global efforts, particularly in vulnerable regions.

At the regional level, Africa continues to face a critical food security crisis, with millions at risk of worsening hunger due to ongoing conflicts, climate variability, and economic instability (IFPRI, 2023). The continent is lagging behind in achieving Sustainable Development Goal 2 (Zero Hunger) as well as the Malabo Declaration target of ending hunger by 2025 (FAO, 2011).

At the national level, Kenya reflects these broader challenges despite policy interventions such as Vision 2030 and the Big Four Agenda, which prioritize food and nutrition security. The country was ranked 86th out of 113 countries in the Global Food Security Index in 2017 and 84th out of 107 countries in the Global Hunger Index in 2020, indicating a serious hunger situation (GOK, 2018; GHI, 2020). Moreover, nearly half of households in counties such as Homa Bay experience food insecurity, highlighting persistent spatial and socio-economic inequalities (KDHS, 2023).

At the household level, food security becomes a lived experience, shaped by a household's ability to consistently access sufficient, safe, and nutritious food. This level is particularly important for empirical analysis, as it captures the direct outcomes of broader global, regional, and national dynamics.

Conceptually, the FAO (2008) defines food security based on four key pillars. The first is availability, referring to the physical presence of food determined by production, stocks, and trade. The second is access, which encompasses both economic and physical ability to obtain food, influenced by income levels, market conditions, and food prices. The third is utilization, which relates to how the body uses nutrients, influenced by dietary diversity, food preparation, health status, and care practices. The fourth is stability, which ensures that availability, access, and utilization are sustained over time without disruption. Food insecurity arises when one or more of these pillars is compromised.

While the concept of food security is broad and multidimensional, its empirical assessment requires measurable indicators that capture household-level outcomes. Assessing food security therefore involves selecting appropriate indicators that reflect one or more of the four pillars (Cafiero et al., 2013). However, there is no universally accepted single indicator, as each measure captures different dimensions of food security (Carletto et al., 2014).

In this study, food security is operationalized at the household level using three complementary indicators: the Food Insecurity Experience Scale (FIES), Household Dietary Diversity Score (HDDS), and Food Consumption Score (FCS). These indicators were selected to capture different dimensions of food security, particularly access and utilization.

The FIES, developed by the FAO, consists of eight questions that assess households' access to adequate food based on their experiences over a specified period and is widely used in population-based surveys (FAO, 2023). The HDDS measures the diversity of foods consumed by a household over a reference period, typically 24 hours or 7 days, and serves as a proxy for dietary quality and nutrient adequacy (Swindale and Bilinsky, 2006). Lastly, the FCS evaluates household dietary quality by analyzing the frequency, diversity, and nutritional value of foods consumed over the previous seven days, assigning weights to different food groups based on their nutritional importance (FAO, 2023).

Together, these measures provide a comprehensive assessment of household food security by combining experiential, dietary diversity, and consumption-based approaches, thereby aligning the conceptual framework with empirical measurement.

1.2.2 Factors influencing food security

Despite significant advancements in technology, mechanization, and access to agricultural resources, Africa's agricultural sector continues to face major challenges, including a high food import bill despite having ample uncultivated land. Initiatives such as the Agricultural Transformation Agenda and the Comprehensive Africa Agriculture Development Programme (CAADP) have aimed to address productivity constraints. However, progress remains uneven across countries and regions, with variations in input use, capital intensity, and agro-ecological conditions contributing to disparities in productivity and technological advancement (DeVries, 2017; Benin, 2014).

Enhancing the productivity of smallholder farms in sub-Saharan Africa is critical for reducing rural poverty and meeting rising food demand by leveraging resources already available to farming households (Paloma, 2020). Achieving food and nutrition security requires substantial investment in agricultural systems, as growth in the sector has largely been driven by land expansion rather than productivity improvements (Djoumessi, 2022). The transformation of Africa's agricultural sector therefore depends heavily on smallholder farmers, who form a significant proportion of the population and produce most of the continent's food (DeVries, 2017; Asenso-Okyere, 2012).

At the household and farm level, several constraints limit productivity and food security outcomes. Smallholder farmers in countries such as Kenya, Tanzania, and Ethiopia face low incomes and limited access to credit, extension services, and markets, which hinder their ability to adopt improved technologies (FAO, 2015; Asfaw, 2012). In Kenya specifically, the crop sub-sector struggles to meet domestic demand for key staples such as maize, wheat, and rice, leading to a heavy reliance on imports (KALRO, 2023). Addressing these challenges requires the development and dissemination of improved agricultural technologies and practices to enhance productivity and competitiveness in staple food production (Wordofa, Hassen, & Endris, 2021).

In addition, climatic and environmental factors significantly influence food security. In Kenya's arid and semi-arid lands (ASALs), which cover approximately 80% of the country's landmass and host about 28% of the population, recurrent droughts and erratic rainfall have contributed to persistent food insecurity (KDHS, 2023). For instance, below-average cereal production, with harvests estimated at about 50% below average for consecutive seasons, has exacerbated food shortages (CGIAR, 2020; FAO-GIEWS, 2022; UNHCR & World Bank, 2021).

Sustainable Agricultural Practices (SAPs) have been identified as critical in addressing these challenges and improving food security outcomes. SAPs refer to farming methods that enhance productivity while conserving the environment, improving soil health, and strengthening resilience to climate change (FAO, 2021). Key practices include conservation agriculture, agroforestry, crop diversification, integrated pest management, organic farming, water conservation techniques such as rainwater harvesting and drip irrigation, and soil fertility management practices like composting and cover cropping. These practices contribute to improved yields, reduced environmental degradation, and enhanced resilience of farming systems.

Food security is therefore influenced by a combination of interconnected factors, including socio-economic factors (such as income, access to credit, and market access), institutional factors (such as extension services and policy support), environmental factors (such as climate variability and rainfall patterns), and technological factors (such as adoption of improved and sustainable agricultural practices).

In this study, the analysis focuses specifically on selected key determinants of food security at the household level. These include access to agricultural inputs and services (credit, extension, digital information, and markets), adoption of Sustainable Agricultural Practices (SAPs), and selected socio-economic and environmental characteristics of households. These factors are hypothesized to influence household food security outcomes, which are measured using the Food Insecurity Experience Scale (FIES), Household Dietary Diversity Score (HDDS), and Food Consumption Score (FCS).

1.2.3 Overview of Homa Bay County

Homa Bay County is located in the former Nyanza region of western Kenya, along the southern shores of Lake Victoria. It borders Kisumu County to the north, Siaya County to the northwest, Migori County to the south, and Kisii and Nyamira counties to the east, while Lake Victoria forms its western boundary (KDHS, 2023). The county covers an approximate area of 3,183.3 km^2, including both land and water surface, and plays a significant role in the regional economy through agriculture and fisheries. According to the Kenya Demographic and Health Survey (KDHS, 2023), about half of the population in Homa Bay County experiences food insecurity, making it one of the most vulnerable counties in Kenya.

Administratively, Homa Bay County is divided into eight sub-counties, namely: Homa Bay Town, Ndhiwa, Rangwe, Suba North, Suba South, Mbita, Karachuonyo, and Kasipul. These sub-counties are further subdivided into wards and locations, forming the basis for local governance and agricultural extension service delivery. The population is predominantly rural, with the majority of households depending on smallholder agriculture and fishing as their main sources of livelihood.

The county experiences a bimodal rainfall pattern, with long rains occurring between March and May and short rains between October and December. However, rainfall is often erratic and unreliable, contributing to frequent crop failures and food shortages. The main agro-ecological zones range from lower midland zones to marginal areas, which are characterized by declining soil fertility and increasing land fragmentation due to population pressure. These climatic and environmental conditions significantly influence agricultural productivity and food security outcomes in the region.

Agriculture is the backbone of the county’s economy, with most households engaged in subsistence farming (KDHS, 2023). Cereals such as sorghum, millet, maize, and rice are commonly cultivated, alongside legumes such as beans and groundnuts. In addition, households practice mixed farming systems that include livestock keeping (such as cattle, goats, and poultry) and fishing activities along Lake Victoria, which contribute to both food availability and household income. Despite this potential, most of the land is dedicated to subsistence production, with limited commercialization.

Although the county has the potential to produce sufficient food for its population, only about 11% of arable land is utilized for crop production (KDHS, 2023). This underutilization is attributed to several constraints, including limited access to agricultural inputs, inadequate extension services, low adoption of improved technologies, and financial limitations among smallholder farmers (FAO, 2015; Asfaw, 2012). Furthermore, agricultural productivity remains low, with average yields estimated at approximately 5 bags per acre for rice, and about 2 bags per acre for both maize and sorghum (90 kg per bag). These yields are significantly below national potential levels, reflecting inefficiencies in production systems and vulnerability to climatic shocks.

Food insecurity in Homa Bay County is both seasonal and structural in nature. The most severe food shortages typically occur between July and August and from December to March, when household food stocks are depleted and reliance on market purchases increases (Asfaw, 2012). During these periods, many households experience reduced food consumption, limited dietary diversity, and increased vulnerability to malnutrition. This situation is exacerbated by poverty, fluctuating food prices, and limited income-generating opportunities, which constrain household access to adequate food.

In addition, the county faces broader structural challenges similar to those observed in other parts of sub-Saharan Africa, including climate variability, land degradation, and limited investment in agricultural systems (Djoumessi, 2022; IFPRI, 2023). Recurrent droughts and erratic rainfall patterns have particularly affected crop production, especially in marginal areas, further deepening food insecurity.

Improving food security in Homa Bay County therefore requires a multifaceted approach that focuses on increasing agricultural productivity and enhancing resilience among smallholder farmers. Key strategies include the adoption of Sustainable Agricultural Practices (SAPs), such as conservation agriculture, crop diversification, agroforestry, and improved soil and water management techniques, which have been shown to enhance productivity while maintaining environmental sustainability (FAO, 2021). Additionally, improving access to extension services, credit facilities, agricultural inputs, and market infrastructure is essential for enhancing farm productivity and household incomes.

Moreover, the integration of modern agricultural technologies, including improved seed varieties, irrigation systems, and digital agricultural information services, can play a crucial role in addressing productivity constraints and reducing vulnerability to climate shocks. Strengthening institutional support and aligning county-level interventions with national policies such as Vision 2030 and the Big Four Agenda can further enhance food security outcomes in the region. According to the Kenya National Bureau of Statistics (KNBS, 2019), the three selected sub-counties have a total of 98,578 cereal-producing farming households, distributed as follows: Suba North (29,766 households), Karachuonyo (41,809 households), and Rangwe (27,003 households). These households formed the target population of cereal-producing farmers for this study.

Overall, Homa Bay County presents a typical case of a high-potential yet underperforming agricultural region, where food insecurity persists due to a combination of climatic, socio-economic, and institutional factors. Understanding these dynamics is critical for designing targeted interventions aimed at improving household food security, which is the focus of this study.

1.3 Statement of the Problem

Maintaining adequate food security remains a persistent challenge for many households in developing countries, particularly in rural settings such as Kenya. Despite global and national efforts to improve food systems, a significant proportion of the population continues to face limited access to sufficient, safe, and nutritious food. In Kenya, food insecurity remains widespread, with notable disparities across regions and counties, and areas such as Homa Bay County experiencing particularly high levels of vulnerability (KNBS, 2018; KDHS, 2023). This persistent condition, despite ongoing policy interventions such as Vision 2030 and the Big Four Agenda, underscores a critical disconnect between policy efforts and actual household-level food security outcomes.

The core problem is not only the persistence of food insecurity, but also the limited understanding of how emerging agricultural transformation strategies specifically agricultural mechanization, digital agriculture technologies, and sustainable agricultural practices jointly influence household food security. While previous interventions have largely focused on increasing production and improving access to food, there remains insufficient empirical evidence on whether and how these modern agricultural approaches translate into improved food security outcomes at the household level, particularly among smallholder farmers.

Although several studies have examined food security in Kenya, much of the existing literature has focused on socio-economic and demographic determinants, livelihood strategies, or regional comparisons. These studies, while valuable, tend to treat food security in isolation from key transformative drivers such as mechanization, digital agricultural technologies, and sustainable farming practices. Furthermore, most studies have analyzed these factors independently rather than examining their combined or complementary effects on food security outcomes.

In addition, there is limited context-specific evidence focusing on cereal-producing households in high food-insecure regions such as Homa Bay County. Given that cereal production forms a critical component of household food systems in rural Kenya, understanding the factors that influence productivity and food access within this sub-sector is essential. However, empirical research that integrates technological, environmental, and institutional dimensions of agriculture in explaining food security outcomes in such contexts remains scarce.

Therefore, the key research problem addressed in this study is the lack of integrated empirical evidence on how agricultural mechanization, digital agriculture technologies, and sustainable agricultural practices influence household food security among cereal producers in Homa Bay County. By focusing on these interconnected drivers, this study provides a more comprehensive understanding of the pathways through which agricultural transformation can improve food security outcomes at the household level.

1.4 Research Objectives

1.4.1 General Objective

The general objective of this study is to determine the effects of agricultural mechanization, agricultural information technologies, and sustainable agricultural practices on food security among households in Homa Bay County, Kenya.

1.4.2 Specific Objectives

i. To assess the influence of agricultural mechanization on food security among cereal farmers in Homa bay County.
ii. To determine the effect of innovative agricultural information technologies on food security among cereal producers in Homa Bay County.

iii. To determine the effect of sustainable agricultural practices on food security among cereal farmers in Homa Bay County.

1.4.3 Research Questions

i. What is the influence of agricultural mechanization on food security among cereal farmers in Homa Bay County?

ii. What is the effect of innovative agricultural information technologies on food security among cereal producers in Homa Bay County?

iii. What is the effect of sustainable agricultural technologies/practices on food security among cereal farmers in Homa Bay County?

1.5 Scope of the study

The study was conducted in Homa Bay County, Kenya, and focused on small-scale cereal producers cultivating less than five acres of land. The target population comprised smallholder farming households engaged in cereal production, from whom data was collected to assess the influence of agricultural mechanization, agricultural information technologies, and sustainable agricultural practices on household food security. The study covered the 2023/2024 production period.

A mixed research design was adopted, using a multistage sampling procedure to select respondents. Data were analyzed using both descriptive statistics and regression analysis to determine the relationship between the selected agricultural practices and food security outcomes at the household level.

1.6 Significance of the study

Ensuring food security is fundamental to poverty reduction, improved human development, and overall socio-economic stability at household, community, national, and global levels. In Kenya, food insecurity remains a persistent challenge, with a significant proportion of the population experiencing moderate to severe food insecurity, and the country ranking relatively low in global food security indices (GHI, 2017). Addressing this challenge requires a deeper understanding of key agricultural drivers such as mechanization, agricultural information technologies, and sustainable farming systems, particularly among smallholder farmers who form the backbone of food production.

Despite existing literature on food security determinants in Kenya, limited empirical attention has been given to the combined influence of agricultural mechanization, information technologies, and sustainable agricultural practices on food security outcomes, particularly at the household level in Homa Bay County. This study therefore contributes to filling this gap by examining how these agricultural innovations influence food security among cereal-producing households.

The findings of this study are expected to provide evidence to support policymakers at both national and county levels in strengthening strategies that promote the adoption of farm mechanization, digital agricultural technologies, and sustainable farming practices. In particular, the results may inform the implementation of existing frameworks such as the Food and Nutrition Security Policy by providing context-specific insights on improving household food security outcomes in rural farming communities.

In addition, the study provides practical value to smallholder cereal farmers by generating evidence on effective agricultural practices that can improve productivity and food access. This enhances farmers' awareness and supports informed decision-making at the community level.

Finally, the study contributes to the existing body of knowledge by addressing a key empirical gap on the interaction between mechanization, agricultural information technologies, and sustainable agricultural practices in relation to food security. It also provides context-specific evidence from Homa Bay County, thereby strengthening the literature on food security in marginal rural settings.

1.7 Organization of the Thesis

This thesis is organized into five chapters. Chapter One introduces the study, including the background, problem statement, objectives, research questions, scope, significance, and overall structure. Chapter Two reviews relevant literature, identifies research gaps, and presents the conceptual framework. Chapter Three outlines the research methodology, including design, sampling, data collection, analysis, and ethical considerations. Chapter Four presents the study results from descriptive and inferential analysis. Chapter Five provides the discussion of findings, summary of findings, conclusions, contributions, recommendations, limitations, and suggestions for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This presents an overview of the existing literature related to the research topic, outlining the key theories, concepts, and findings that shape current understanding in the field. It examines major trends and debates while identifying gaps or inconsistencies that justify the need for further investigation. By situating the study within this broader academic context, the chapter establishes the foundation for the proposed research and highlights its potential contribution to existing knowledge.

2.2 Theoretical Review

The study was based on two theories: Production and random utility.

Production theory

Production Theory, originally advanced by Adam Smith (1776) and later formalized in neoclassical economics, explains how inputs are combined to produce outputs through a production function. At its core, the theory is based on several key tenets: first, that output is a function of multiple inputs such as land, labour, capital, and technology; second, that the relationship between inputs and output can be systematically analysed using a production function; third, that changes in input combinations lead to variations in output levels; and fourth, that efficiency in production depends on the optimal allocation and use of available resources under constraints such as cost, technology, and access.

In the agricultural context, these tenets imply that farm output and ultimately food security is determined by how effectively farmers combine and utilize production inputs. Inputs such as labour, land, capital, and technology interact to influence productivity, meaning that improvements in any of these components can potentially enhance output levels. This theoretical foundation directly supports this study by providing a framework for analysing how agricultural mechanisation, agricultural information technologies, and sustainable agricultural practices act as key production inputs that influence agricultural output and household food security. Agricultural mechanisation represents the capital-intensive component of production, improving efficiency in land preparation, planting, and harvesting, thereby increasing productivity when optimally utilized. Agricultural information technologies function as a knowledge and decision-support input, improving farmers' access to real-time information on weather, markets, and agronomic practices, which enhances resource allocation and reduces production inefficiencies. Sustainable agricultural practices represent a productivity-enhancing input that maintains soil fertility, conserves resources, and ensures long-term stability of output. From a production theory perspective, food security is therefore an outcome of the production process, influenced by the interaction of these inputs under varying household and environmental constraints. Differences in access to mechanisation, digital agricultural tools, and sustainable farming practices lead to differences in productivity, which in turn affect food availability, access, and stability at the household level.

Thus, Production Theory provides the analytical basis for this study by explaining how variations in agricultural input use and technology adoption translate into differences in farm productivity and ultimately household food security outcomes in Homa Bay County.

Random Utility Theory

Random Utility Theory (RUT), developed from the work of Thurstone (1927) and later formalized by Marschak (1960) and McFadden (1974), is grounded on key tenets of decision-making under uncertainty. The theory assumes that individuals are rational decision-makers who choose among alternative options by comparing the utility derived from each option. It further posits that utility is composed of two components: a deterministic (observable) component that reflects measurable factors influencing choice, and a random (unobservable) component that captures unmeasured influences and individual-specific preferences. A central tenet of the theory is that individuals select the alternative that provides the highest expected utility, although the presence of unobserved factors makes choice outcomes probabilistic rather than purely deterministic.

This study adopts Random Utility Theory because it provides a strong behavioral foundation for understanding farmers' adoption decisions regarding agricultural technologies and practices. In this context, farmers are assumed to make rational choices between adopting or not adopting agricultural mechanization, agricultural information technologies, and sustainable agricultural practices based on the perceived utility or net benefits associated with each option.

Applied to this study, mechanization, digital agricultural information technologies, and sustainable agricultural practices are viewed as alternative production-enhancing options from which farmers derive different levels of utility depending on their circumstances. A farmer will adopt a given technology or practice if the expected benefits such as increased productivity, reduced labor costs, improved access to information, or enhanced sustainability outweigh the associated costs and constraints.

The theory also assumes that observed adoption behavior is influenced by both observable and unobservable factors. Observable factors include socioeconomic characteristics (such as income, education, and farm size), institutional factors (such as access to extension services and credit), and market conditions. Unobservable factors include individual preferences, risk attitudes, perceptions, and expectations, which collectively contribute to differences in adoption decisions among farmers.

Therefore, Random Utility Theory is appropriate for this study as it explains the decision-making process underlying the adoption of agricultural mechanization, digital agricultural technologies, and sustainable agricultural practices, which are the key explanatory variables influencing household food security outcomes in Homa Bay County.

2.3 Empirical Review of Literature

This sub-section presents the empirical review of literature, focusing on studies that have investigated the research topic through data-driven methods and real-world observations. It summarizes key findings from previous empirical research, highlights the methodologies used and identifies consistent patterns or contrasting results across studies.

2.3.1 Agricultural Mechanization and Food Security

Empirical literature widely recognizes agricultural mechanization as an important driver of agricultural productivity and food security through improved efficiency, reduced labour constraints, and enhanced timeliness of farm operations. Diao et al. (2016) define agricultural mechanization as the use of tools, implements, and powered machinery to improve farm productivity and efficiency, noting its positive contribution to yields and income improvement. Similarly, FAO & AUC (2018) emphasize that mechanization enhances labour productivity, increases incomes, reduces poverty, and alleviates the drudgery associated with farming.

A number of studies further support the productivity benefits of mechanization. Deng et al. (2020) highlight improvements in efficiency, cost savings, and output quality, while Li et al. (2017), Yao (2009), and Luo & Qiu (2021) note reduced labour costs and improved profitability. In addition, Tian et al. (2020) argue that mechanized farming is more cost-efficient compared to manual labour, while He et al. (2018) and Nam et al. (2021) show that mechanization improves land preparation and input efficiency.

However, despite these benefits, findings across contexts reveal important variations. While mechanization is well developed in countries such as China, the USA, and Germany (Pingali, 2007; Wang et al., 2016), its adoption in developing countries remains constrained. Mrema et al. (2018) note that mechanization improves labour efficiency and reduces post-harvest losses, but Binswanger-Mkhize (2013) highlights persistent barriers such as high costs, limited credit access, and poor infrastructure in developing regions.

In Sub-Saharan Africa, mechanization remains low despite its potential. Van Loon et al. (2020) and FAO (2016) report limited adoption, while Diao et al. (2016) emphasize continued reliance on traditional farming methods. Even where mechanization exists, it is unevenly distributed across countries such as Ghana, Ethiopia, and Nigeria, where government interventions have attempted to promote adoption (Takeshima, 2017). Evidence from Kenya and other African countries shows that mechanization can improve yields and timeliness of farm operations (Daum, 2023; Yukichi et al., 2017; Adu-Baffour et al., 2019), but these studies largely focus on productivity outcomes rather than direct food security impacts.

In Kenya, mechanization remains low, with only about 30% of agricultural activities mechanized (Ministry of Agriculture, 2022), and smallholder tractor ownership estimated at only 5% (Bymolt & Zaal, 2015). Although mechanization is recognized as important for food security (KALRO, 2023), most existing studies do not empirically link mechanization to household food security outcomes using multidimensional indicators.

The key gap is the limited empirical evidence on how agricultural mechanization influences household food security among smallholder cereal producers, particularly in vulnerable counties such as Homa Bay, and the lack of econometric analysis linking mechanization directly to food security outcomes.

2.3.2 Agricultural Informational Technologies and Food Security

Digital Agricultural Information Technologies (DAIT) refer to the use of digital tools and platforms to enhance agricultural productivity, efficiency, and decision-making through improved access to information, markets, and services (World Bank, 2019). These include mobile advisory services, precision agriculture technologies, AI-based systems, and digital marketplaces.

Globally, DAIT has been associated with improved productivity and resource efficiency. Zhang et al. (2020) report that digital innovations such as mobile advisory services and precision agriculture have transformed farm productivity, while FAO (2020) and Pingali et al. (2019) show that high-income countries such as Germany, China, and the USA have benefited from improved yields and reduced losses through digital agriculture tools. Similarly, Galvez (2022) highlights improved resilience and productivity in Asia-Pacific countries due to digital platforms and technologies.

In Africa, adoption of DAIT is increasing due to mobile penetration and demand for real-time agricultural information (Aker et al., 2016). Platforms such as M-Farm in Kenya and Esoko in Ghana have improved access to market and weather information, enhancing productivity (Baumüller, 2018). Empirical evidence shows positive impacts on yields and efficiency, including Nakimuli et al. (2021) who report a 30% increase in productivity in Uganda, Murendo et al. (2018) who found a 25% maize yield increase in Zimbabwe, and Aker and Ksoll (2019) who report reduced post-harvest losses in Nigeria.

In Kenya, studies such as Okello et al. (2020) and Nakasone et al. (2019) confirm positive effects of digital advisory services and credit platforms on productivity and financing access. However, constraints such as poor infrastructure, limited connectivity, and high costs continue to limit adoption (Nyarko et al., 2021). Platforms such as DigiFarm have shown broad benefits in income, resilience, and market access (Makini et al., 2018; CGIAR, 2020), yet evidence remains largely productivity-focused.

Despite these advances, research in Kenya has largely concentrated on maize production and general productivity outcomes, with limited attention to food security outcomes across different cereal systems. Furthermore, there is a lack of studies assessing the impact of multiple DAIT platforms on household food security in specific vulnerable regions such as Homa Bay County.

The key gap is the limited empirical evidence linking agricultural information technologies directly to household food security outcomes using multidimensional indicators such as HDDS, FIES, and FCS in smallholder cereal farming systems.

2.3.3 Sustainable Agricultural Practices and Food Security

Sustainable Agricultural Practices (SAPs) are widely recognized as farming approaches that enhance productivity while preserving natural resources. According to FAO (2021), SAPs include conservation agriculture, agroforestry, crop diversification, and integrated pest management, all of which improve soil fertility, water conservation, and ecosystem resilience. Pretty et al. (2018) also highlight their role in increasing yields and ensuring long-term food security.

However, empirical findings show mixed results regarding their direct impact on food security. While van Ittersum et al. (2016) show that SAPs such as conservation agriculture and agroforestry improve yields and household food availability, Mbow et al. (2019) note that adoption remains low due to financial and knowledge constraints. Justice and Jonathan (2018) further show that conservation agriculture improves soil structure, water retention, and yields, while Nkala et al. (2011) find improved productivity but limited direct food security impact in Mozambique. In contrast, Abdulai (2016) reports improved maize productivity and reduced poverty in Zambia.

In Kenya, Kinyua et al. (2020) show that SAPs improve soil fertility and yields in selected regions, but most studies focus on maize production and specific practices such as conservation agriculture or agroforestry. Evidence on broader SAP combinations remains limited. Additionally, while global evidence shows increasing adoption of sustainable intensification (Pretty & Jules, 2018), adoption in Africa remains constrained by financial and institutional challenges (Mbow et al., 2019). Large-scale projects such as Galana-Kulalu further illustrate inconsistent productivity outcomes due to environmental shocks such as flooding and climate variability (KIPPRA, 2021), reinforcing the need for resilient farming systems.

The key gap is the limited empirical evidence on the combined effect of multiple SAPs on household food security in smallholder cereal systems, particularly in under-researched regions such as Homa Bay County, and the lack of integrated econometric analysis linking SAPs to food security outcomes.

2.4 Summary of Literature and Research Gaps

The literature review as shown various empirical studies and reports regarding the variables under study in various nations across SSA. Table 2.1 presents the gaps in a clear and structured format, making it easier to identify the areas that require further research.

Table 2-1: Knowledge and research gaps summary

Thematic Area	Existing Research	Gaps Identified
Food Security Status (Global & Kenya)	• Studies explore food security trends, challenges, and agricultural innovations globally and in Kenya. • Mutea et al., 2022; Waswa et al., 2012; Ingutia and Sumelius, 2022; Gwada et a1., 2020.	• Lack of models integrating socio-economic factors, climate variability, and regional disparities. • Limited granularity in existing models, making them ineffective for localized contexts. • Need for real-time data integration for predictive responses to food security threats.
Agricultural Mechanization & Food Security	• National-level studies on mechanization exist, focusing on maize production and tractor distribution. • Diao et al., 2016; Deng et al.,2020; Yao, 2009; Luo and Qiu, 2021; Tian et a2013; Van; He et al., 2018; Nam 2016; TakeshimaLiu and Zhou, 2018; Jiquan, 2022 Pingali, 2007; Wang et al., 2016; Mrema et al., 2018; FAO, 2020; Ababio et al., 2019; Mrema et al., 2014; Heimduo, 2016; Binswanger-Mkhize, 2013;Van Loon et al., 2020;FAO, 2016;Takeshima, 2017;Daum, 2023; Yukichi et al., 2017; Adu-Baffour et al., 2019; Daum, 2020; Mrema et al., 2020; Berhane et al., 2020; Takeshima & Lawal, 2020; FAO & AUC, 2018; KNBS, 2021;MoAL&F, 2022; Sheahan and Barrett, 2017; MoAL&F, 2015;Mutua et al.,2014; Bymolt and Zaal, 2015.	• Limited research on mechanization's impact on non-maize cereals in Homa Bay County. • Absence of studies modeling mechanization's direct impact on food security using indicators like animal drought power, tractor usage, HDDS, FIES, and FCS.
Digital Agricultural Information	• Global studies highlight developed economies, focusing	• Limited research on Digital Agricultural Information Technologies deployment in developing regions.

Technologies & Food Security	on advisory services and market access. • African studies emphasize mobile-based solutions. • World Bank, 2019;Zhang et al., 2020;FAO, 2020; Pingali et al., 2019; Galvez, 2022; Aker et al., 2016; Baumüller, 2018; Nakimuli et al., 2021; Murendo et al., 2018; Aker and Ksoll, 2019; Connelly, 2021; Baumüller, 2018;AMA & Chando, 2021;Van Loon et al., 2020; Okello et al., 2020); Nakasone et al., 2019; Nyarko et al., 2021; Makini et al., 2018; Makini et al., 2018; CGIAR, 2020.	• Lack of econometric modeling to quantify Digital Agricultural Information Technologies' impact on food security. • Neglect of Digital Agricultural Information technologies' influence on diverse staple crops beyond maize.
Sustainable Agricultural Practices (SAPs) & Food Security	• Extensive global research on SAPs, primarily in developed economies, focusing on agronomic perspectives. • Studies at national and regional levels in Africa and Kenya. • FAO, 2021; Pretty et al., 2018); Jules and Zareen, 2014; Thomson et al., 2012; Milder et al.,2012; Ittersumm et al., 2016; Mbow et 1995; Njukie and Jonathan, 2018; Nkala et al., 2011; Abdulai, 22012018; Theis al.2018.5; Arslan et al.,2014;, FAO, 2017; Mazvimavi and Twomlow, 2009; Gracious and Diiro, 2021; Lodin et al., 2014; Kassie et al., 2018; Nguezet et al., 2011; Lokossou et al., 2015; Paris and Pingali, 1995; Njuki et al., 2014; Fisher et al., 2000; Carney and Carney, 2018; Theis et al., 2018;Kinyua et al., 2020; FAO, 2018; Pretty & Jules, 2018; Somasundaram et al., 2017; KIPPRA, 2021.	• Gaps in understanding SAPs in low-resource environments. • Lack of econometric models assessing SAPs' direct impact on food security indicators (HDDS, FIES, FCS). • Overemphasis on maize, with limited studies on sorghum, millet, and rice. • Scarcity of localized research in Homa Bay County, accounting for socio-economic and environmental factors.

Source: (Researcher, 2025)

2.5 Conceptual framework

Figure 2.1 illustrates the interplay of various determinants of the adoption of agricultural mechanization, digital agricultural information technologies, and sustainable agricultural practices. Smallholder farmers exhibit diverse socio-economic characteristics such as family size, marital status, gender, age, schooling level, livestock ownership, income, technology awareness, and individual perception that impact their adoption decisions. Additionally, institutional characteristics, including credit access and group membership, significantly influence these choices. Farm-specific attributes, such as land size and tenure, also affect the likelihood of adopting these agricultural innovations, ultimately influencing household food security.

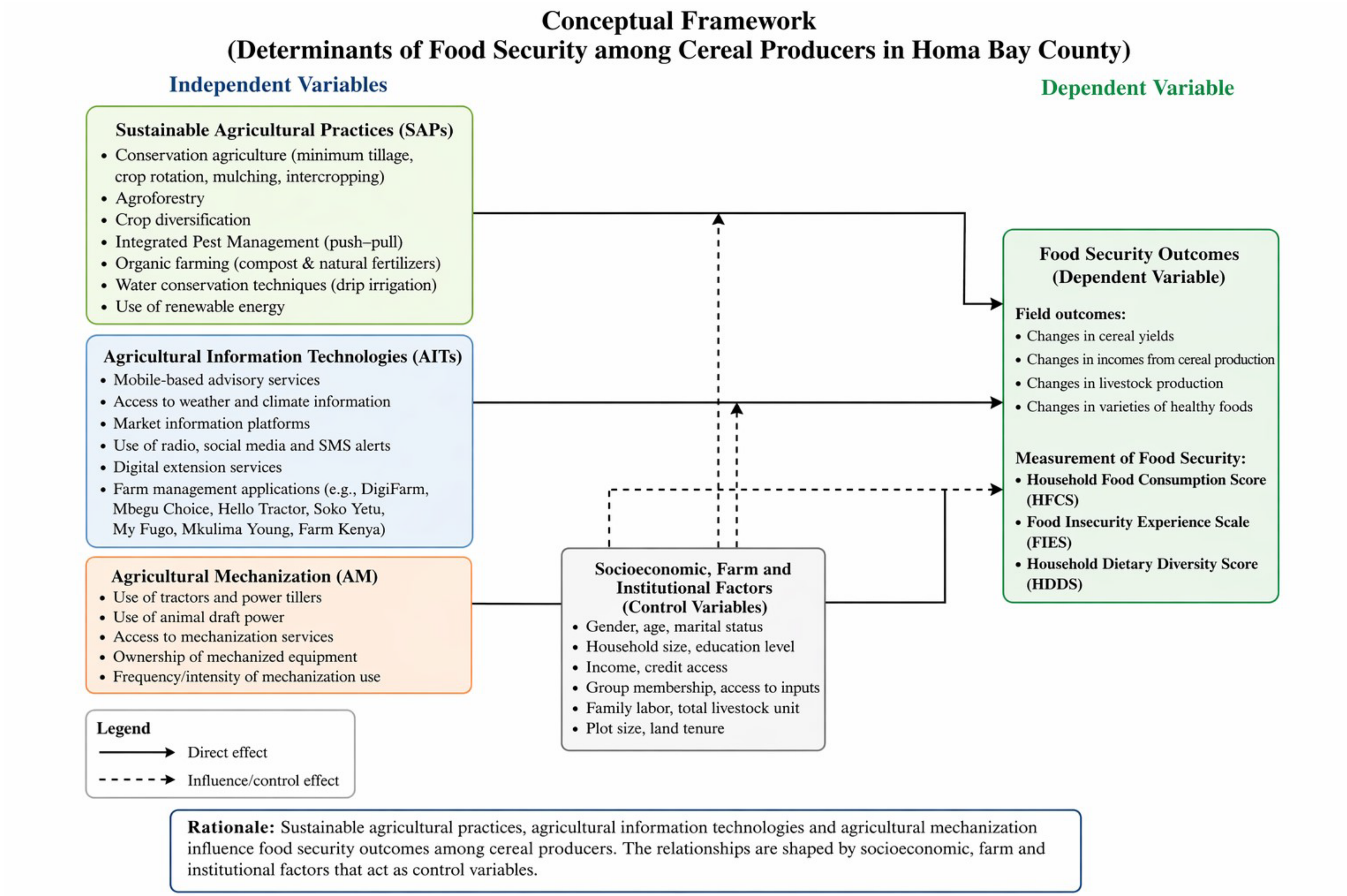

Figure 2-1: Conceptual framework (Researcher 2025)

2.6 Operationalization of the Variables

Table 2-2: Operationalization of the Variables

Study Variable	**Operational Definition**	**Measurement / Indicators (Operationalization)**	**Method of Statistical Analysis**
Dependent Variable			
Food Security	Household food security is defined as the level of physical, economic, and social access to sufficient, safe, and nutritious food that meets dietary needs for an active and healthy life. It is measured as a multidimensional index capturing food access and dietary adequacy.	Constructed using validated food security indicators: • **Food Consumption Score (FCS)** – dietary diversity and frequency weighted score • **Food Insecurity Experience Scale (FIES)** – experience-based access constraints • **Household Dietary Diversity Score (HDDS)** – number of food groups consumed in 24 hours Combined into an index or used as separate outcomes depending on model	• Descriptive statistics (mean, distribution of food security levels) • Propensity Score Matching (impact of adoption on food security outcome) • Ordered Logistic Regression (if food security is categorized: Severe food insecurity/Moderate food insecurity /Mild food insecurity/ Food security /moderate/high) • Poisson/Negative Binomial Regression (for count-based indicators such as HDDS)
Independent Variable			
Agricultural Mechanization	Agricultural mechanization refers to the extent of use of mechanical or non-human power technologies in farming operations including	Categorical adoption variable defined as: • 0 = No mechanization • 1 = Partial mechanization (use of either tractor or animal traction	• Descriptive statistics (adoption rates) • Propensity Score Matching (effect of mechanization

	land preparation, planting, weeding, irrigation, and harvesting.	in at least one farming activity) /Full mechanization (use of tractor/animal traction in multiple key operations)	adoption on food security outcomes)
Digital Agricultural Information Technologies (DAITs)	DAITs adoption is defined as the use of digital platforms and communication technologies that provide agricultural information, market access, advisory services, and decision support to farmers.	Binary measure based on adoption of digital tools such as: • Mbegu Choice, Hello Tractor, DigiFarm, Soko Yetu, Mkulima Young, Farm Kenya , etc • SMS weather alerts, radio, social media agricultural content **Operational rule:** 0 = No DAITs use 1 = Use of ≥2 platforms	• Descriptive statistics (adoption patterns) • Ordered Logistic Regression (if food security is categorized: Severe food insecurity/Moderate food insecurity /Mild food insecurity/ Food security /moderate/high)
Sustainable Agricultural Practices	Sustainable agricultural practices refer to environmentally friendly farming methods that enhance productivity while conserving natural resources and ensuring long-term soil and ecosystem health under climate variability.	Composite adoption index based on practices including: • Conservation agriculture (minimal tillage, crop rotation, mulching, intercropping) • Agroforestry • Crop diversification • Integrated Pest Management (IPM) • Organic fertilization (compost/manure)	• Descriptive statistics (mean adoption intensity, at least 3 practices) • Poisson Regression (for count-based indicators such as HDDS)

		• Water conservation (drip irrigation) • Renewable energy use (solar irrigation) **Score:** Number of practices adopted categorized as adoption of at least 3 practices	

2.7 Chapter Summary

This chapter introduced the literature review and discussed the empirical studies selected for this research. It provided definitions of food security, its measurement, and its status globally and in Kenya. Additionally, it presented an empirical study reviews on the factors determining food security at global, regional, and national levels, with a specific focus on Kenya and Homa Bay County. The chapter critically examined the influence of agricultural mechanization, digital agricultural information technologies, and SAPs on food security. It also identified research gaps from the literature review and provided justification for the study. Furthermore, it discussed the theoretical framework, emphasizing production theory and random utility theory.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the study design and the methodology applied in conducting the research. It describes the research design and underlying philosophy, the target population, sampling frame, sample size and sampling procedures, data collection methods and instruments, as well as the approaches used for data analysis and presentation.

3.2 Research Philosophy

Research philosophy refers to a bundle of beliefs and assumptions that guide how knowledge is developed in a research process (Easterby-Smith et al., 2012). It defines research view the world and influences their choice of methods, techniques, and strategies for conducting research. This study is guided by a pragmatic research philosophy. Pragmatism was selected because it supports the use of methods that best answer the research questions rather than committing to a single philosophical position. Given the complexity of food security determinants among cereal producers in Homa Bay County, Kenya, a pragmatic approach allows for the integration of both quantitative and qualitative evidence to generate a comprehensive and practically relevant understanding.

Under this approach, quantitative data is used to examine observable and measurable relationships between key variables such as technology adoption, agricultural practices, and food security outcomes, enabling statistical generalization of findings. At the same time, qualitative data is used to capture farmers' lived experiences, perceptions, and contextual factors that explain how and why certain food security outcomes occur. This combination ensures both breadth and depth in analysis.

The pragmatic philosophy is therefore appropriate for this study as it supports the mixed-methods design adopted, allowing methodological flexibility and the integration of different forms of evidence to strengthen interpretation and policy relevance. It also ensures that the study remains focused on practical problem-solving in addressing food insecurity among small-scale farmers..

3.3 Research Design

Research design refers to the overall framework that guides the process of collecting, measuring, and analyzing data in a study (Sileyew, 2019). It provides a structured plan for addressing research objectives through appropriate data collection and analysis procedures.

This study adopted a descriptive cross-sectional research design. This design was appropriate because it allows for the collection of data at a single point in time to describe the characteristics of the study population and examine the relationships between key variables as they naturally occur (Bougie & Sekaran, 2016). In this study, the design was used to assess the determinants of food security among cereal farmers in Homa Bay County, including farm characteristics, access to agricultural inputs, climate-related factors, market access, and adoption of agricultural technologies and practices.

The descriptive cross-sectional design was particularly suitable because it enables the study to identify patterns and associations between variables without manipulating them or establishing strict causality. This is consistent with the study's objective of understanding the factors associated with food security outcomes among farmers.

Quantitative data were collected and analyzed to summarize and examine relationships among variables using appropriate statistical techniques, while qualitative data from Key Informant Interviews (KIIs) and Focus Group Discussions (FGDs) were used to provide contextual explanations of farmers' experiences and perceptions regarding food security determinants and challenges. This combination enhanced the depth of interpretation and helped to validate quantitative findings through triangulation. Overall, the descriptive cross-sectional design provided a practical and effective framework for generating evidence on food security determinants among cereal farmers in Homa Bay County.

3.4 Study Area, Population and Sampling Design

3.4.1 Study Area and Population

The study population refers to all individuals or units that share the characteristics of interest to which the study findings are intended to be generalized (Shukla, 2020). In line with the study objectives outlined, the target population comprised cereal-producing farming households in Homa Bay County, Kenya.

Homa Bay County has eight sub-counties, namely: Suba North, Suba South, Rangwe, Karachuonyo, Ndhiwa, Homa Bay Town, Rachuonyo North, and Rachuonyo South. However, this study focused on three sub-counties: Suba North (Mbita), Rangwe, and Karachuonyo. These sub-counties were purposively selected because they fall within the dominant cereal-producing livelihood zones of the county, specifically the Central Cotton and Sorghum Zone and the Lake Shore Fishing and Irrigated Agriculture Zone, where maize, sorghum, and rice farming are the main agricultural activities (Acidri, Machuki, & Seaman, 2018). The sub-counties experience a bimodal rainfall pattern, receiving between 250 mm and 1,200 mm of rain annually, supporting diverse crop and livestock farming.

The selection of these sub-counties was also based on their relevance to the study variables, particularly the presence of cereal production systems affected by climate variability, soil fertility challenges, and differing levels of agricultural technology adoption. This ensured that the study population adequately represented farmers engaged in cereal production systems relevant to the research problem.

According to the Kenya National Bureau of Statistics (KNBS, 2019), the three selected sub-counties have a total of 98,578 cereal-producing farming households, distributed as follows: Suba North (29,766 households), Karachuonyo (41,809 households), and Rangwe (27,003 households). These households formed the target population of cereal-producing farmers for this study.

In addition, in Rangwe Sub-county, specifically within the Oluch-Kimira Irrigation Scheme, there are over 369 registered water users engaged in rice production across twelve irrigation blocks (Ouma et al., 2020). These formed part of the rice-producing sub-population within the broader cereal farming system. Farmers were considered eligible for inclusion based on their active engagement in cereal farming (maize, sorghum, or rice), farming experience, and involvement in relevant agricultural practices under investigation. Data from the Homa Bay County Department of Agriculture was used to identify active and experienced cereal farmers across the selected sub-counties.

3.4.2 Sampling Design

A sample referred to a small fraction of the target population chosen through appropriate sampling techniques. Given that the proportion of cereal producers in the county was known, the study sample size was calculated using a proportionate household sampling method (Kothari, 2018).

$$n = \frac{z^2(p)(1-p)}{e^2}$$

Where; n is sample size; z is 95% confidence level set at is 1.96, p is the fraction of cereal producers in the population set at 0.5 (50%) and $1 - p$ is the fraction of non-producers set at 0.5 (50%). Again, e is the degree of precision or the allowable margin of error which is 0.05(5%). This gave a sample size of 384 respondents. To account for anticipated non-response, incomplete questionnaires, and possible data loss during data cleaning, a 20% sample size adjustment was applied. This adjustment is consistent with survey research practice in household-based studies, where non-response and unusable responses are commonly expected. The inflation also ensured that the final dataset retained sufficient statistical power and representativeness for subgroup analysis across the selected sub-counties after proportional allocation.

Based on this adjustment, the sample size was increased to approximately 461 respondents, who were then proportionately distributed across the selected sub-counties to ensure balanced representation and improve the reliability of the study findings. Due to the homogeneity and spread of target study population over a county region, the data adopted proportionate stratified random sampling to give equal chance of each sub-counties to be presented in the collection of data as shown in Table 3.1 below.

Table 3-1:Sample size distribution for each sub county

	Rangwe	**Karachuonyo**	**Suba North**	**Total**
Total cereal producers	27,003 (27%)	41,809	29,766	98,578
Total sample	126	196	139	461

A sampling procedure is the approach used to select several individuals to gather information regarding a certain population from which they were selected (Chiuri, King'ori, & Obara, 2020). The study adopted both probability and non-probability sampling techniques to create a sample size for study. Probability sampling was used to randomly select cereal producers for quantitative survey across the selected sub-counties. Non-probability sampling techniques was utilized to select key informants and famers to participate in qualitative interviews as KIIs and FGD.

The sampling frame comprised all households engaged in the production of maize, sorghum, and rice within the selected study areas in Homa Bay County. A multistage stratified random sampling technique was used to select a total of 473 households, slightly above the minimum required sample of 461 to account for field realities such as non-response and incomplete responses.

In the first stage, Homa Bay County was purposively selected because it is among the regions in Kenya experiencing persistent food insecurity, declining soil fertility, and increasing climate variability, all of which directly affect cereal production systems. This makes it a relevant context for studying food security determinants.

In the second stage, three sub-counties (Suba North, Karachuonyo, and Rangwe) were purposively selected. The selection was guided by their prominence in cereal production systems (maize, sorghum, and rice) and their representation of different agricultural production environments within the county. These sub-counties were also identified from county agricultural reports as key cereal-producing zones, ensuring that the study captured areas where the target farming systems are concentrated rather than assuming uniform conditions across the county.

In the third stage, one ward from each sub-county was purposively selected with the assistance of agricultural officers and village leaders: Kochia Ward (Rangwe), Gembe Ward (Suba North), and Kibiri Ward (Karachuonyo). The selection was based on documented predominance of cereal farming activities and accessibility of farming households engaged in maize, sorghum, or rice production. This ensured that the study focused on wards with high relevance to the research variables rather than assuming homogeneity across all wards.

In the fourth stage, three villages per selected ward were randomly selected from official village lists provided by local administration offices, resulting in a total of nine villages. Random selection at this stage ensured that household selection remained statistically unbiased within the purposively selected wards. The number of villages per ward was also guided by logistical considerations such as accessibility and cost efficiency.

Finally, a complete list of farming households within the selected villages was compiled with the help of local leaders. From this list, households engaged in cereal farming were randomly selected to form the final study sample. The selected farmers were reached and visited on their homestead. The selection strategy intentionally focused on areas with documented cereal production systems and varying agricultural conditions, allowing for more realistic representation of farming contexts within the county.

Table 3-2: Distribution of achieved sample size

	Rangwe	Karachuonyo	Suba North	Total
Total sample targeted	126	196	139	461
Total sample size achieved	135	198	140	473
Achievement (%)	107%	101%	101%	103%

This sampling approach ensured a fair distribution of farmers was based on the type of cereal produced while maintaining the integrity of the data collection process.

For the Key Informant Interviews (KIIs), three Ward Agricultural Officers, one from each of the selected wards (Kochia, Gembe, and Kibiri), were purposively selected. These officers were chosen due to their technical expertise and direct involvement in implementing agricultural programmes and supporting farmers within the study area. Their selection was considered appropriate because they provide informed perspectives on agricultural practices, food security interventions, and institutional challenges affecting cereal production in the county.

For the Focus Group Discussions (FGDs), a total of three FGDs were conducted, one in each selected ward, involving cereal farmers. Each FGD consisted of 6–10 participants, who were purposively and conveniently selected with the assistance of village leaders to ensure representation across gender, age, and farming experience. The sample size for FGDs was guided by qualitative research standards, where groups of this size are considered sufficient to encourage active participation while maintaining manageability and depth of discussion.

The decision to conduct three FGDs (one per ward) was informed by the principle of thematic saturation, where data collection is continued until no new themes or significant insights are emerging across groups. Given that participants were drawn from relatively similar farming contexts within the selected cereal-producing wards, it was anticipated that saturation could be reasonably achieved within this number of discussions. This approach ensured both depth and efficiency in capturing farmers lived experiences, perceptions, and coping strategies related to food security and agricultural practices.

3.5 Data Collection Methods

This sub-section outlines the procedure that was used to get data from respondents. Data was obtained from both secondary and primary sources. For instance, the primary data collection techniques included KIIs with Ward Agricultural Officers, cross-sectional household survey, and FGDs with cereal farmers. Secondary data were gathered through a desktop review of relevant literature, reports, and databases. A semi-structured questionnaire was adopted for face-to-face structured interviews with selected participants during the household survey (see Appendix 1). This method was preferred because it is both time-efficient and effective in collecting well-structured quantitative and qualitative data that can be systematically analyzed (Kothari, 2018).

The questionnaires were administered with the assistance of trained data enumerators. To ensure clarity, validity, reliability, and ease of use, the data collection tools were pre-tested. The pre-testing was conducted in all the three sub-counties with a randomly selected sample of 9 farmers (3 per sub-county). This process helped in refining the instruments by identifying and correcting potential errors while also served as a training exercise for the enumerators prior to the actual data collection (Mugenda & Mugenda, 2019). Physical interviews were preferred approach, as they facilitated a more interactive process, allowing respondents to engage in a relaxed environment. This method also helped in establishing rapport with participants, clarified the purpose of the study, and minimized potential negative attitudes toward participation. Data collected from cereal farmers using the questionnaire included household demographic and socio-economic characteristics, such as age, gender, education, household size, income, land ownership, and access to services (credit, markets, and extension). The study also gathered information on agricultural mechanization (types of machinery used, ownership, and application), agricultural information technologies (awareness, usage, access, and perceived usefulness of digital platforms), and sustainable agricultural practices (types of practices adopted and duration of use). In addition, detailed data on household food security were collected using established indicators, including food consumption, dietary diversity, food expenditure, and experiences of food insecurity.

To enhance efficiency and accuracy, the questionnaire was digitized using the KOBOCollect app, enabling data collection via mobile phones or tablets. Enumerators received training on how to use the KOBOCollect application for seamless data entry. A KII guide was used to gather in-depth insights from ward agricultural officers involved in agricultural initiatives within the county. These interviews were conducted by the researcher himself. FGD guide was also used to facilitate FGDs, capturing cereal farmers' perceptions, experiences, and attitudes regarding food security, agricultural technology, and farming practices. Farmers for the FGDs were purposively and conveniently selected, ensuring diversity in gender and age representation. These FGDs was conducted by the researcher himself. Complementary qualitative data from KIIs and FGDs provided insights into farmers' experiences, perceptions, and institutional perspectives on the role of mechanization, technology, and sustainable practices in influencing food security. Secondary data were gathered from sources such as government reports, newsletters, unpublished documents and online databases, to complement the primary data.

3.6 Research Quality

The quality of this research was achieved through rigorous methodological design, reliability and validity testing, digital data collection, and adherence to ethical standards. A well-structured sampling strategy was employed to ensure a representative sample, reducing bias and enhancing generalizability.

3.6.1 Reliability

Reliability refers to the consistency and stability of the data collection instrument across different respondents and contexts. In this study, reliability was ensured through a structured pre-testing and standardization process. The questionnaire was pre-tested with nine farmers (three from each of the selected sub-counties: Rangwe, Karachuonyo, and Suba North) to assess clarity, question flow, and consistency of interpretation. Feedback from the pre-test informed revisions, including refinement of ambiguous questions, removal of redundancies, and improvement of question sequencing.

To ensure consistency in administration, enumerators were trained on the survey instrument and data collection procedures, emphasizing uniform understanding and application of the questionnaire. In addition, the use of KoboCollect enhanced reliability through built-in validation checks, skip logic, and real-time error controls, which minimized inconsistencies during data entry.

The study also achieved a high response rate (90%), reducing the likelihood of non-response bias and supporting the stability of the dataset.

3.6.2 Validity

Validity refers to the extent to which the instrument accurately measures the intended study variables. In this study, validity was enhanced through expert review, pilot testing, and data triangulation. The questionnaire was reviewed by subject matter experts to ensure content relevance and alignment with the study objectives, while the pre-test helped confirm clarity and appropriateness of the questions.

Triangulation of data sources including household surveys, Key Informant Interviews (KIIs), Focus Group Discussions (FGDs), and secondary data further strengthened the credibility of the findings by allowing cross-verification of information.

The use of KoboCollect also supported validity by incorporating skip patterns and validation rules that ensured logical consistency and reduced entry errors. Callbacks were also implemented in areas where clarifications were needed from the farmer. This helped improve accuracy and completeness of the data collected, thereby enhancing the overall quality of the study.

3.7 Data Analysis

Data analysis was conducted using both quantitative and qualitative approaches in line with the study's mixed-methods and correctional design. Quantitative data from household surveys were coded, cleaned, and analysed using SPSS and STATA. Data cleaning involved checking for completeness, consistency, and accuracy, as well as handling missing or inconsistent responses.

Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarise household characteristics, levels of technology adoption, and food security indicators. To examine relationships between variables, inferential statistical techniques were applied. These included Propensity Score Matching (PSM) to assess the effects of adoption of agricultural mechanization and technologies on food security outcomes, ordered logistic regression for analysing ordinal outcomes such as food security status, and Poisson regression models for count-based variables such as dietary diversity and adoption intensity. These methods were selected based on the nature of the dependent variables and are consistent with approaches used in similar empirical studies.

Qualitative data from Key Informant Interviews (KIIs) and Focus Group Discussions (FGDs) were analysed using thematic analysis. The data were transcribed, coded, and organised into themes based on recurring patterns and concepts related to agricultural practices, technology use, and food security experiences. The qualitative findings were used to complement and explain quantitative results, providing deeper insights and supporting interpretation through triangulation. Overall, the integration of quantitative and qualitative analysis enabled a more comprehensive understanding of the determinants of food security among cereal farmers. Specific analytical model, is explained as follows:

Objective 1: To determine the effect of agricultural mechanization on food security among cereal farmers in Homa bay County

Both descriptive and matching analysis were adopted to analyze this objective. PSM helped in addressing endogeneity and sample selection bias in examining the linkages between adoption of farm mechanization and other explanatory variables, following the confoundedness assumption. Additionally, it is well-suited for single cross-sectional datasets, as in this study (Heckman et al., 1998). Propensity Score Matching was applied to assess the effect of agricultural mechanization uptake, which is measured as a binary variable (adopter vs. non-adopter). Since farmers are not randomly assigned to adopt mechanization, there is a risk of selection bias arising from observable differences such as farm size, income, or access to services. PSM was therefore selected because it creates comparable groups of adopters and non-adopters with similar characteristics, allowing for a more reliable estimation of the impact of mechanization on food security outcomes.

The PSM method matched observations of users and non-users based on their predicted probability scores or likelihood of using agricultural mechanization. This approach replicated the randomized experiment conditions, allowing for the causal-effect to be evaluated similarly to a controlled experiment. By ensuring that all observable characteristics are accounted for, PSM treated agricultural mechanization adoption as a random assignment, making it not related with food security outcome indicators, specifically the Household Food Consumption Score (Smith & Todd, 2005). To obtain reliable results, systematic differences in outcomes between users and non-users due to unmeasured attributes were eliminated through conditioning, as demonstrated below by Smith and Todd (2005).

A represented a binary variable for agricultural mechanization adoption status where A_i = 1 was if i^{th} cereal producer adopted agricultural mechanization (tractor or animal drought power), and A_0 = 0, was otherwise. In addition, let Y_{1i} and Y_{2i} showed expected observed food security outcomes for agricultural mechanization user and non-user respectively. Then treatment effect, TE was.

$TE = Y_{1i}$ - Y_{2I} ……………………………………………………..…………….………. ...(5)

Equation 5 presented the treatment effect or influence of agricultural mechanization technology uptake on the i^{th} producer. Since we only see;

$Y_i = A_i Y_{1i} + (1 - A_I) Y_{2I}$ ………………………...……………………...……..……......(6)

Instead of Y_{1i} and Y_{2I} for same producer, we found it cumbersome to get treatment effect for every producer. Therefore, we calculated the average effect of treatment on the treated, ATT as shown in equation 8 (Becker and Ichino, 2002).

$ATT = E(Y_{1i} - Y_{2i} / A_i = 1)$ ……………………………………………………………….(8)

The propensity scores for agricultural mechanization adoption was then determined as shown in equation 9 (Rosenbaum and Rubin, 1983);

$\Pr ob(X) = \Pr ob(A_i = 1/X)$ ………………………………………………...….………….(9)

Based on the conditional independence assumptions, $Y_{1i}, Y_{2i} \perp A/X$ the potential food security outcomes were independent of agricultural mechanization adoption given X which represented vector of independent variable (see Table 1), which implied that,

$E(Y_{2i} / A = 1, \Pr ob(X)) = E(Y_{2i} / A = 0, \Pr ob(X))$ ……………………………………...….(10)

and

$0 \prec \Pr ob(X) \succ 1$ …………………………………..…………………………….…………..(11)

For all X , there was a positive likelihood of either using agricultural mechanization ($A = 1$) or not uptaking ($A = 0$) as this guarantying every agricultural mechanization users a counterpart in the non-users population, thus resulting ATT can be estimated as;

$$ATT = E(Y_{1i} - Y_{2i} / A_i = 1) \quad (12)$$

$$ATT = E[E(Y_{1i} - Y_{2i} / A_i = 1, \Pr ob(X))] \quad (13)$$

$$ATT = E[E(Y_{1i} / A_i = 1, \Pr ob(X)) - E(Y_{2i} / A_i = 0, \Pr ob(X))] \quad (14)$$

Smith and Todd (2005) noted that since scores are continuous variables, it was impossible to find an agricultural mechanization user with the exact same score to serve as a counterfactual, making equation 13 inadequate for calculating the average treatment effect. To achieve the robustness of the estimated findings, it was necessary to apply multiple matching methods. Therefore, this study utilized kernel and three nearest neighbor matching methods to verify the reliability and consistency of the estimates. PSM was employed to evaluate and compare the effect, or average treatment effect (ATE), of agricultural mechanization application on smallholder household food consumption scores. It was calculated by assigning weights to various food groups based on their nutritional importance and summing the weighted frequencies to generate a total score, which categorizes farming families into poor, borderline, or acceptable food consumption levels.

Objective 2: To determine the effect of innovative digital agricultural information technologies uptake on food security among cereal farmers in Homa Bay County

Descriptive statistics and ordered logit regression were adopted to determine the impact of innovative agricultural technologies on food security in Homa Bay County. Ordered logistic regression was used to analyse food insecurity measured using the Food Insecurity Experience Scale (FIES), which is inherently an ordered categorical variable (e.g., food secure, mildly insecure, moderately insecure, severely insecure). This model is appropriate because it accounts for the natural ranking of these categories without assuming equal distances between them, making it suitable for examining how explanatory variables influence the likelihood of households falling into different levels of food insecurity.

This objective considered HFIES as a measure of food security. HFIES is a globally recognized tool used to assess how severe is food insecurity situation at household based on people's experiences and perceptions. It assessed uncertainty about food access, reductions in food quality and quantity, and extreme food deprivation over a reference period, specifically the past twelve months. The scale consisted of eight standardized questions, ranging from worrying about food running out to staying for an entire day without taking food because of limited or absence of resources. Responses were categorized into different levels of food insecurity, from mild to severe, (3 =Food security to mild food insecurity, 2=Moderate food insecurity and 1=Severe food insecurity) providing valuable iinformation into the behavioral and psychological impacts of food shortages. The HFIES is widely used by researchers, policymakers, and humanitarian organizations to monitor food insecurity trends, design interventions, and evaluate the effectiveness of food security programs.

Because the dependent variable (HFIES) are ordinal, they represent a ranked classification of food security levels, making the ordered logistic regression model an appropriate choice for analyzing the factors affecting food (in) security in cereal-producing households. As explained by Wooldridge (2002), the ordered logit regression model expands upon the conditional logistic model by incorporating numerous threshold points to determine the factors influencing a household's probability of falling into a higher food security category. Household food (in) security is shaped by both observable and unobservable factors. Consequently, the ordered logit regression model was used to estimate the dependent variable, categorizing families based on their status of food security as follows.

For HFIES;

1=Severe food insecurity
2=Moderate food insecurity
3 = Mild food insecurity
4=Food security

Following Wooldridge (2002), if y was an ordered response, taking values 1,2,3,4, and y^* was the latent value representing expected utility of y, then ordered logistic model for y (conditional on explanatory variables x_i and certain unobservable factors ε_i) was derived from a latent variable model as follows:

$$y_i^* = x_i \beta_i + \varepsilon_i \tag{15}$$

The j cutoff point was given as $\mu_a \prec \mu_b \prec \mu_c$ such that:

$$y_i = \begin{cases} 1\ (severely\ food\ insecure), if\ y_i^* \leq \mu_a, \\ 2\ (moderately\ food\ insecure), if\ \mu_a\ \leq y_i^* \leq \mu_b, \\ 3\ (Mildly\ food\ insecure), if\ \mu_b\ \leq y_i^* \leq \mu_c, \\ 4\ (Food\ secure)\ if\ y_i^* \geq \mu_c \end{cases} \quad (16)$$

The model also assumed 0 mean and a static variance. The vector of estimated regressors parameters was represented in the vector of coefficient, which included market, farm-related, socio-economic, and institutional variables (Wooldridge, 2002; Greene, 2008). Greene (2008) noted that the ordered logit regression model effectively fits a propensity curve by employing a normal distribution function to estimate the likelihood of a household falling into a specific ranked category. This ordered model was chosen since the dependent variables are ordinal and influenced by multiple independent factors. Additionally, it provided efficient and robust estimates. The coefficients of the model was interpreted by assessing the marginal impact of regressors on the expected value of the dependent variable. In Equation (15), the outcome variable represented different categories of household of food security. The explanatory variables included the level of adoption of digital and innovative agricultural information technologies i.e adoption of at least two DAIT i.e Mbegu Choice, Hello Tractor, DigiFarm, Soko Yetu, My Fugo, Mkulima Young, Farm Kenya, radio, social media, and SMS-based weather alerts. To determine the influence of digital and innovative agricultural information technologies adoption on food security, this study considered a binary option variable of whether a producer was adopting at least two of the following digital platforms (Mbegu Choice, Hello Tractor, DigiFarm, Soko Yetu, My Fugo, Mkulima Young, Farm Kenya, radio, social media, and SMS-based weather alerts) (Adoption=1) or not (Non-adoption=0). It was expected that market, farm, socio-economic, and institutional variables would have either a negative or positive impact on food security.

Objective 3: To determine the effect of SAPs on food security among cereal farmers in Homa Bay County.

To address this objective, both descriptive analysis and Poisson regression were employed. Poisson regression was employed to analyse the Household Dietary Diversity Score (HDDS), which is a count variable representing the number of food groups consumed by a household. Count data are non-negative integers and often exhibit skewed distributions, making Poisson-based models appropriate. These models allow for the estimation of how explanatory variables influence changes in the number of food groups consumed, thereby providing insights into factors affecting dietary diversity. Poisson regression is a technique designed for modeling count data, where the dependent variable reflects the frequency of an event occurring within a defined time frame or space. The Poisson regression model is derived from the Poisson distribution, which is defined as:

$$P(Y = y) = \frac{e^{-\tau}\tau^{y}}{y!}, y = 0, 1, 2, 3 \ldots \qquad \text{(17)}$$

where:

- Y - dependent variable was the HDDS, a count measure representing the number of different food groups consumed by a household within a specified reference period, usually 24 hours or seven days. HDDS was used as a proxy for dietary quality, access to food, and overall nutritional adequacy, where higher scores indicate more diverse diets and improved household food security.
- τ was the expected count (mean) of events occurring in a given time or space.
- e was the natural logarithm base.

The mean and variance of a Poisson-distributed variable were equal (τ), making it suitable for modeling count data. The Poisson regression model expresses the expected count τi for observation i as a function of independent variables.

$$\tau_i = \exp(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots .. + \beta_k X_{ki}) \qquad \text{(18)}$$

Taking the natural logarithm on both sides results in a log-linear model**:**

$$\log(\tau_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots .. + \beta_k X_{ki} + e \qquad \text{(19)}$$

Where

- τ_i was the expected count for observation i i.e HDDs
- β_0 Was the intercept.
- β_k were the coefficients giving the effect of regressors X_{ki} on the expected count i.e socio-economic, farm, institutional characteristics and sustainable agricultural practices
- was the error term.

Sustainable agricultural practices was model as a binary variable where 1 represent adoption of at least 3 of the following sustainable agricultural practices: conservation agriculture (minimal tillage, crop rotation, mulching, intercropping) agroforestry, crop diversification, IPM, organic farming (compost and natural fertilizers), Water conservation techniques (drip irrigation), renewable energy sources (solar-powered irrigation, and 0 if not/otherwise.

This study too utilized qualitative data from KII and FGDs to complement and enrich the quantitative findings. KIIs with agricultural officers helped in explaining observed patterns in technology adoption, market access, and policy effectiveness, while FGDs with farmers captured community perceptions, experiences, and challenges that may not be fully captured through structured tools. Thematic analysis of qualitative data was applied alongside statistical analysis to identify emerging patterns and triangulate findings. This mixed-method approach enhanced the validity as well as reliability of the research.

3.8 Ethical Issues in Research

The study was conducted in full compliance with ethical standards, including obtaining informed consent and ensuring voluntary participation, confidentiality, and anonymity. Respondents were assured that no personally identifiable information would be disclosed or shared without their permission, and explicit consent was obtained before taking or using any photographs. Prior to data collection, ethical approval was secured from the Strathmore University Institutional Ethics Review Committee (SU-IERC) and a research permit obtained from the National Commission for Science, Technology, and Innovation (NACOSTI). Relevant local authorities were also notified and their authorization obtained to support community entry and engagement. An official university introductory letter was attached to the data collection tools to explain the study objectives and reaffirm participants' rights. In addition, enumerators were trained on ethical research conduct, including respect for participants, cultural sensitivity, confidentiality, and secure handling of data. The study complied with all applicable regulations and was implemented only after receiving the necessary institutional and administrative approvals.

3.9 Chapter Summary

This chapter summarizes the research methods, design and data collection approaches. It begins by describing the philosophical approach to this study. Then it presents research designs where both qualitative and quantitative methods were used to analyse and develop the effect- cause relationships of the variables. It then discusses the population, sampling approaches, achieved sample size, and data collection process that were applied. The chapter proceeds to discuss the variables of the quality of research discussing both reliability and validity aspects of this study, Data analysis process and ethical procedure applied during the research period are also presented.

CHAPTER FOUR
RESEARCH FINDINGS AND INTERPRETATION

4.1 Introduction

This chapter presents the results and findings of the study, guided by the three specific objectives. The analysis explores the influence of farm mechanization on food security, examines the effect of innovative agricultural information technologies on food security among cereal producers, and evaluates how SAPs contribute to food security outcomes. The results are organized thematically in line with the study objectives, pinpointing key linkages, patterns, and relationships that originated from the data.

4.2 Response Rate

The survey recorded a strong overall response rate across all sub-counties. Rangwe exceeded its target with a 107% achievement, collecting 135 responses against the 126 targeted. Karachuonyo and Suba North also slightly surpassed their targets, each achieving 101% of their expected samples. Overall, the study attained 473 responses against the targeted 461, reflecting an impressive total achievement rate of 103%, indicating high participant cooperation and effective fieldwork implementation.

4.3 Demographic Information

The study sample consisted of 473 farmers drawn from three sub-counties: Rangwe, Suba North, and Karachuonyo (Table 4.1).

Table 4-1: Gender of sampled farmers by sub-county

Sub-county	Sample size/ Percent	Gender of the farmer		
		Male	Female	Total
Rangwe	N	60	75	135
	%	44.4	55.6	100
Suba North	N	88	52	140
	%	62.9	37.1	100
Karachuonyo	N	103	95	198
	%	52.0	48.0	100
Total	N	251	222	473
	%	53.1	46.9	100

The socio-economic profile of respondents reveals important structural characteristics that shape agricultural decision-making and food security outcomes. The sample was slightly male dominated (53.1%), although gender distribution varied across sub-counties, with Rangwe showing a female majority (55.6%) while Suba North had a higher proportion of male farmers (62.9%) (Table 4-1). This variation suggests that gender roles in agriculture differ spatially, which may influence access to resources such as land, mechanization, and information. Qualitative findings further highlighted this disparity, with one female farmer in Rangwe noting: *"We do most of the farm work, but decisions like buying equipment or selling produce are often made by men."* This indicates potential intra-household dynamics that may affect adoption of technologies and overall farm productivity.

Table 4-2: Distribution of sampled farmers by targeted cereal value chains

Sub counties	Sample size/ Percent	Percent of sampled farmers growing target cereal value chain			
		Maize	Sorghum	Rice	Millet
Rangwe	N	135	102	23	41
	%	100	75.56	17.04	30.37
Suba North	N	134	62	0	0
	%	95.71	44.29	0	0
Karachuonyo	N	153	58	35	1
	%	77.27	29.29	17.68	0.51
Total	N	422	222	58	42
	%	89.22	46.93	12.26	8.88

Crop production patterns show a strong dominance of maize (89.2%), followed by sorghum (46.9%), while rice (12.3%) and millet (8.9%) remain less common and geographically concentrated (Table 4-2). The near-universal cultivation of maize, particularly in Rangwe and Suba North, suggests heavy reliance on a single staple, which may expose households to production and climate risks. In contrast, the higher adoption of sorghum and millet in Rangwe indicates some level of crop diversification in more climate-vulnerable areas. During FGDs, farmers emphasized this adaptation strategy: *"Sorghum survives when maize fails because of drought, so we plant both to be safe."* This reflects an awareness of climate variability and the role of crop choice in managing risk.

The socio-economic, farm, institutional, and food security characteristics of the respondents are presented below.

Table 4-3: Socio-Economic Characteristics of Respondents

Variables	Description	N	Percent/Means
Marital status of the respondent (%)	Married	376	79.49
	Single	12	2.54
	Divorced/Separated	2	0.42
	Widow/Widower	83	17.55
Age of the respondent (%)	18-35 years	86	18.18
	36-49 years	197	41.65
	Above 49 years	190	40.17
Education level of the respondent (%)	No education	26	5.50
	Adult education	11	2.33
	Primary	241	50.95
	Secondary	130	27.48
	Tertiary (College and universities)	65	13.74
Main occupation of the respondent (%)	Farming (crop/livestock)	381	80.55
	Formal/Salaried employment	33	6.98
	Farm employment (Casual laborer elsewhere	8	1.69
	Non-farm employment (Casual laborer elsewhere)	13	2.75
	Self Employed (Trader/Businessman)	38	8.03
Average total annual on farm income (KES)		473	48491.82
Average total annual off-farm income (KES)		473	53612.05
Average total annual income (KES)		473	102103.90
Person responsible for final family decisions on how household income is spent (%)	Self	201	42.49
	Jointly (spouse and self)	262	55.39
	Respondent and other household member jointly.	9	1.90
	Spouse only	0	0.00
	Nonrelatives i.e workers	1	0.21
Person responsible for final family decisions on household purchases (%)	Self	195	41.23
	Jointly (spouse and self)	261	55.18
	Respondent and other household member jointly.	16	3.38
	Spouse only	0	0.00
	Other household members/relative	1	0.21
	Non relatives i.e workers	0	0.00

Most respondents were married (79.49%), above 35 years (81.82%), and had primary-level education (50.95%), with farming as the main occupation (80.55%). The relatively older farming population and low levels of higher education suggest limited exposure to advanced agricultural innovations and digital technologies, which may constrain adoption of modern practices. Farmers also reported an average of 16.98 years of farming experience, indicating strong experiential knowledge but not necessarily alignment with improved or modernized practices. One key informant observed: *"Farmers have experience, but many still rely on traditional methods because they lack training on newer technologies."*

Table 4-4:Nature of Land tenure

Variables	Description	N	Percent/Means
Total agricultural land available (acres)		473	2.85
Whether respondent owns 100% of total agricultural land available (%)	No	124	26.22
	Yes	349	73.78
Types of land tenure systems if respondent doesn't own 100% of total agricultural land available (%)	Partially owned (Yes)	8	6.45
	Rented (Yes)	34	27.42
	Communal (Yes)	1	0.81
	Public land (Yes)	1	0.81
	Family land (Yes)	94	75.81
Total land fully owned		349	2.78
Average size of land under different types of land tenure systems if respondent doesn't own 100% of total agricultural land available (%)/Size of land under other structure (acres)			
	Partially owned	8	2.00
	Rented	34	3.50
	Communal	1	1.00
	Public land	1	4.00
	Family land	94	3.68

Landholding sizes were relatively small, averaging 2.85 acres, with most cereal cultivation taking place on 1.19 to 2.57 acres. This indicates smallholder-dominated production systems, which often limit economies of scale and mechanization potential.

Table 4-5: Cereal farming experience

Variables	Description	N	Percent/Means
Average years of cereal farming experience		473	15.55
Average years of farming experience		473	16.98
Maize varieties grown (%)	Improved	193	45.73
	Local	168	39.81
	Both	61	14.45
Sorghum varieties grown (%)	Improved	95	42.79
	Local	99	44.59
	Both	28	12.61
Rice varieties grown (%)	Improved	44	75.86
	Local	14	24.14
	Both	0	0.00
Millet varieties grown (%)	Improved	34	80.95
	Local	7	16.67
	Both	1	2.38
Average total land under cereal production (acres)		422	2.57
Average total land under maize production (acres)		422	1.92
Average total land under sorghum production (acres)		222	1.52
Average total land under rice production (acres)		58	1.42

Farmers had substantial experience (16.98 years) in farming, largely practiced cereal farming mainly maize and sorghum with moderate use of improved varieties, under 1.19 to 2.57 acres of land.

Table 4-6: Livestock ownership

Variables	Description	N	Percent/Means
Whether respondent own livestock (%)	No	149	31.50
	Yes	324	68.50
Whether respondent own bulls (%)	Yes	97	29.94
Average number of bulls owned		97	5
Whether respondent own dairy cattle (%)		99	30.56
Average number of dairy cattle owned		99	4
Whether respondent own sheep/goats (%)	Yes	95	29.32
Average number of sheep/goats owned		95	9
Whether respondent own poultry (%)	Yes	234	72.22
Average number of poultry owned		234	17
Whether respondent own donkeys (%)	Yes	20	6.17
Average number of donkeys owned		20	2

Most households owned some livestock (68.50%), particularly poultry (72.22%).

Table 4-7: Market attributes

Variables	Description	N	Percent/Means
Average distance to the nearest market center (Minutes)		473	39.18
Whether respondent have access to markets and other selling outlets (%)	No	66	13.95
	Yes	407	86.05
Whether respondent is member of production and marketing group or association (%)	No	384	81.18
	Yes	89	18.82
Types of production and marketing group or association member participates in (%)	Farmers' Cooperative (Yes)	70	78.65
	Community based organization (Yes)	25	28.09
	Produce aggregation center (Yes)	5	5.62
Farmers' perceived benefits obtained from participation in production and marketing group or association (%)	Business training (Yes)	51	57.30
	Access to affordable and quality inputs (Yes)	41	46.07
	Fair prices for my produce (Yes)	27	30.34
	Access to my extension services (Yes)	25	28.09
Marketing channels used by respondents (Yes, %)	Direct to consumers	319	67.44
	Middlemen/Brokers	170	35.94
	Cooperatives/Agro processors/aggregators	86	18.18
	Retailers	28	5.92
	Wholesalers	6	1.27
	Institutions	11	2.33
	Hotel/restaurants	1	0.21
Whether respondent have access to credit and other loan products (%)	No	274	57.93
	Yes	199	42.07
Whether a farmer had received government subsidy for inputs (%)	No	338	71.46
	Yes	135	28.54

Although market access was relatively high (86.05%), access to critical support services remained low, including extension services (52.64%), credit (42.07%), subsidies (28.54%), and farmer group participation (18.82%). These gaps point to institutional and financial constraints that may hinder productivity and adoption of improved practices. FGDs reinforced this, with one farmer stating: *"Even if you want to improve your farm, getting credit or extension advice is not easy."*

Table 4-8: Food security attributes

Variables	Description	N	Percent/Means
Household size (Number)		473	5
Respondent's rating of household health (%)	Excellent	7	1.48
	Good	262	55.39
	Fair	179	37.84
	Poor	21	4.44
	Very poor	4	0.85
Respondent's perception on household food security status	Food shortage through the year	19	4.02
	Occasional food shortage	295	62.37
	No food shortage but no surplus	152	32.14
	Food surplus	7	1.48
Food Insecurity Experience Scale	Food Secure	99	20.93
	Mild Food Insecurity	78	16.49
	Moderate Food Insecurity	97	20.51
	Severe Food Insecurity	199	42.07
Household Dietary Diversity Score		473	7.35
Household Food Consumption Score	Poor consumption	24	5.07
	Borderline consumption	85	17.97
	Acceptable consumption	364	76.96
Respondent's rating of adequacy of their household food consumption	More than enough	9	1.90
	Just enough	361	76.32
	Not enough	103	21.78

Despite relatively acceptable food consumption levels (76.96%), only 20.93% of households were classified as food secure, indicating a disconnect between short-term food access and long-term food security stability. This suggests that while households may meet immediate consumption needs, they remain vulnerable to shocks such as income fluctuations, climate variability, or market instability. Key informants emphasized this vulnerability: *"Most households can eat today, but they are not secure because one bad season can push them into crisis."*

Overall, these findings highlight that cereal farming households in the study area operate under resource constraints, limited institutional support, and varying socio-economic conditions, all of which shape their production decisions and food security outcomes.

ANALYSIS ACCORDING TO RESEARCH OBJECTIVES

4.4 Influence of Agricultural Mechanization on Food Security in Homa Bay County

This sub-section presents the results and findings of objective one, including descriptive analysis of the farmers, inferential analysis of propensity score matching as well as qualitative findings from respondents.

4.4.1 Descriptive analysis

Table 4-9: Characteristics of Farm Mechanization among Cereal Farmers

Variables	Description	N	Percent
Whether a farmer has mechanized the farm (%)	No	113	23.89
	Yes	360	76.11
Types of farming activities a farmer mainly apply farm mechanization (Yes, %)	Ploughing	358	99.44
	Harrowing	72	20.00
	Planting	49	13.61
	Weeding	23	6.39
	Irrigation	20	5.56
	Harvesting	9	2.50
How farmers mainly acquire the machinery/tools used (%)	Owned	55	15.28
	Hire	305	84.72
	Free	0	0.00

The findings indicate that 76.11% of farmers had mechanized at least one farm operation, suggesting that mechanization is present but highly uneven across farming activities. Mechanization was almost universal for ploughing (99.44%), highlighting its importance as a labor-intensive and time-sensitive activity. However, mechanization levels dropped sharply for other operations such as planting (13.61%), weeding (6.39%), irrigation (5.56%), and harvesting (2.50%). This pattern suggests that mechanization is partial and concentrated at the initial stage of production, rather than being applied across the full farming cycle. Qualitative findings provide further insight into this pattern. Farmers reported that ploughing is prioritized because it requires significant labor and determines the timing of planting: *"If you don't plough on time, you miss the rains, so we hire tractors first before thinking about other activities."* In contrast, operations such as weeding and harvesting are often done manually due to cost constraints and limited access to appropriate machinery: *"Machines for weeding or harvesting are expensive or not available here, so we use family labour."* These responses indicate that cost, availability, and suitability of machinery influence the selective adoption of mechanization. Access to mechanization was predominantly through hiring services (84.72%), with only a small proportion of farmers owning machinery (15.28%), and none accessing equipment free of charge. This reliance on hiring suggests that mechanization is service-based rather than asset-based, which may improve short-term access but can also create challenges related to timing, cost, and availability during peak seasons. Key informants emphasized this constraint: *"Most farmers depend on hired tractors, but during peak periods, demand is high and some are delayed, which affects planting."* Overall, the findings show that while mechanization is widely adopted in principle, its application remains limited in scope, uneven across activities, and constrained by access and affordability factors, which may affect its overall contribution to productivity and food security outcomes.

Table 4-10: Type of machinery

Variables	Description	N	Percent
Type of machinery farmers mainly use in maize production in the last season (%)	Animal traction	135	41.41
	Tractor	191	58.59
	Irrigation equipment	0	0.00
	Harvesting equipment	0	0.00
Type of machinery farmers mainly use in sorghum production in the last season (%)	Animal traction	64	37.87
	Tractor	104	61.54
	Irrigation equipment	1	0.59
	Harvesting equipment	0	0.00
Type of machinery farmers mainly use in rice production in the last season (%)	Animal traction	6	11.76
	Tractor	34	66.67
	Irrigation equipment	11	21.57
	Harvesting equipment	0	0.00
Type of machinery farmers mainly use in millet production in the last season (%)	Animal traction	17	41.46
	Tractor	24	58.54
	Irrigation equipment	0	0.00
	Harvesting equipment	0	0.00
Farmers' perception whether the government subsidize the cost of mechanization (%)	No	277	76.94

	Yes	83	23.06

The results show that tractors are the dominant source of power across cereal production, particularly in rice (66.67%) and sorghum (61.54%) farming systems. This indicates a gradual shift toward modern mechanization, especially in areas where production is more commercially oriented or time-sensitive. However, animal traction remains an important complementary source of power, particularly among farmers with limited financial capacity, suggesting that mechanization pathways are mixed rather than fully modernized. The use of machinery for harvesting was notably low, reinforcing earlier findings that mechanization is concentrated in land preparation rather than across the entire production cycle. Farmers reported that harvesting technologies are either unavailable or too costly to access: *"We can hire tractors for ploughing, but harvesting machines are rare and expensive, so we harvest manually."* This highlights a gap in mechanization services beyond primary operations, which may affect labour efficiency and post-harvest outcomes. In addition, a majority of farmers (76.94%) reported limited access to government mechanization support, including subsidies. This suggests that existing support mechanisms are either insufficient or not effectively reaching smallholder farmers. Key informants echoed this concern, noting: *"Government support for machinery exists, but few farmers actually benefit due to limited coverage and awareness."* The findings indicate that while tractors play a central role in current mechanization practices, dependence on mixed power sources, limited access to harvesting technologies, and weak institutional support constrain the extent to which mechanization can be fully utilized across cereal production systems.

4.4.2 Inferential Analysis

A probit model was used to estimate the probability of mechanization and assess its causal effect on food security, with diagnostic tests conducted to ensure model reliability, including checks for multicollinearity, specification, and heteroskedasticity (See output 1 in Appendix VI). The results showed no multicollinearity (mean VIF = 1.33), but indicated heteroskedasticity and minor model specification issues, justifying the use of robust standard errors for consistent estimation. Overall, despite marginal evidence of omitted variables, the diagnostics suggest that the probit model was adequately fitted and suitable for interpreting the determinants of mechanization with reasonable confidence.

Table 4-11: Results of probit estimation of propensity scores for mechanization adoption

	Coefficient	Robust Standard Errors	z-values	P>z
Gender of the respondent (0=Female, 1=Male)	-0.15	0.15	-0.99	0.32
Marital status of the respondent (0=Not married, 1=Married)	0.56	0.19	2.96	0.00***
Age of the respondent (1=18-35 years, 2=36-49 years, 3=Above 49 years)	-0.15	0.12	-1.27	0.20
Education of the respondent (1=No education, 2=Adult education, 2=Primary, 3=Secondary, 4=Tertiary (College and universities))	-0.01	0.09	-0.12	0.91
Household size	-0.05	0.03	-2.14	0.03**
Years of farming experience	0.02	0.01	2.84	0.01***
Ownership of livestock (0=No, 1=Yes)	0.42	0.15	2.78	0.01***
Main occupation of respondent (0=Non-farming, 1=Farming)	0.25	0.18	1.36	0.17
Total household income (KES, 00,000)	0.00	0.00	2.05	0.04**
Access to credit (0=No, 1=Yes)	-0.04	0.15	-0.29	0.77
Access extension services (0=No, 1=Yes)	0.64	0.15	4.29	0.00***
Constant	-0.25	0.48	-0.52	0.61

Note: Number of observations = 473; LR chi square (11) =59.25; Prob > chi square =0.0000. Log likelihood= -230.43638; Pseudo R2 =0.1139; ***, ** and * denote significant at 1%, 5% and 10% levels, respectively

The probit model assessing mechanization adoption was statistically significant (LR $\chi^2 = 59.25$, $p < 0.001$) and demonstrated a reasonable fit, explaining about 11.4% of the variation in mechanization decisions among 473 cereal farmers. The results show that marital status, household size, farming experience, livestock ownership, access to extension services, and total household income, significantly influenced mechanization adoption ($p < 0.05$). In contrast, gender, age, education level, main occupation, and credit acces were not significant determinants of mechanization adoption in the study area.

Marital status had a positive and statistically significant effect ($\beta = 0.56$, $p < 0.01$), suggesting that married farmers are more likely to adopt mechanization. This may reflect greater household stability and access to pooled resources, which can support investment in farm operations. Qualitative insights support this pattern, with one farmer noting: *"When you have a family, you need to produce more food, so you look for faster ways like using tractors."*

In contrast, household size showed a negative and significant relationship with mechanization adoption ($\beta = -0.05$, $p < 0.05$), indicating that larger households are less likely to mechanize. This suggests that households with more members may rely more on family labour as a substitute for mechanization. Farmers in FGDs confirmed this trade-off: *"If you have many people at home, you* *don't need to hire machines for everything because labour is available."* This highlights how labour availability within households can reduce the perceived need for mechanized services.

Farming experience had a positive and significant influence ($\beta = 0.02$, $p < 0.01$), indicating that more experienced farmers are more likely to adopt mechanization, possibly due to better understanding of its benefits over time. Similarly, livestock ownership was positively associated with mechanization ($\beta = 0.42$, $p < 0.01$), reflecting the role of farm assets in supporting investment capacity, particularly where livestock can complement or substitute mechanized power. Total household income also had a positive and significant effect ($\beta = 0.00$, $p < 0.05$), suggesting that even marginal increases in income improve farmers' ability to access mechanization services.

Notably, access to extension services had a strong positive and statistically significant effect ($\beta = 0.64$, $p < 0.01$), highlighting the critical role of information and institutional support in promoting mechanization. Key informants emphasized this linkage: *"Farmers who interact with extension officers are more likely to try new technologies because they understand the benefits."*

This study used PSM approach, which controls for observable features to isolate the intrinsic effect of mechanization on food consumption scores. A balance test was conducted to ensure that the distribution of relevant covariates between mechanized and non-mechanized farmers was similar before and after matching. The overlap or common support condition was verified through a line graph illustrating the distribution of propensity scores (x-axis) for mechanized (treated) and non-mechanized (untreated) cereal farmers. The identified region ranged from 0.31119972 to 0.99722638, as shown in Figure 4-1 (Also see Output 1 in Appendix VI).

Balancing tests and common support determination

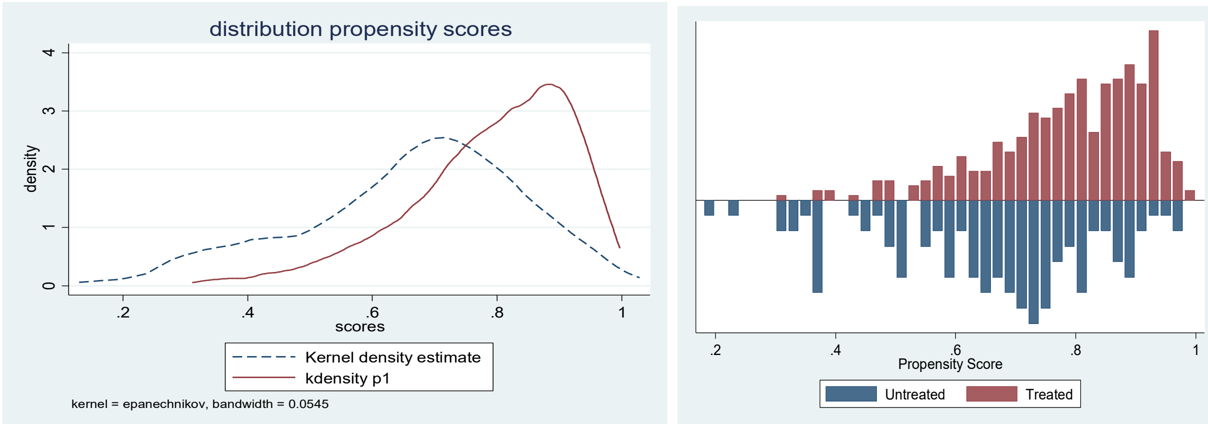

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Figure 4-1: Common support graphs

This condition ensures that comparable household characteristics exist across both treatment and control groups. Examination of the propensity score distributions indicated substantial overlap between the two groups, implying that most mechanized and non-mechanized farmers fell within the common support region. As a result, only a small number of observations were excluded from the analysis, indicating that an appropriate and reliable match was achieved.

Assessing the matching quality

Table 4-12: Propensity score quality indicators

Matching algorithms	Three nearest neighbors Matching NNM (3)	Kernel matching (KM)
Before Matching		
Pseudo R^2 before matching	0.114	0.114
LR chi square before matching	59.25	59.25
Mean standardized bias before matching	21.1	21.1
Prob > chi square	0.000	0.000
After matching		
Pseudo R^2 after matching	0.023	0.019
LR chi square after matching	22.30	19.08
Mean standardized bias after matching	8.8	8.9
Prob > chi square	0.22	0.16
Total % bias reduction	58.29	57.82

To evaluate the quality of matching, a balancing test was conducted to determine whether differences in the explanatory variables as covariates between the matched treatment and control groups had been adequately minimized. In this study, all variables met this criterion, confirming that mechanized and non-mechanized cereal farmers with comparable observable characteristics were successfully matched. Consequently, the three nearest neighbor and kernel matching algorithms were identified as the most suitable techniques, as they produced substantial bias reduction across all covariates. There were no statistically significant differences ($p > 0.05$) in the mean distribution between the treated (mechanized) and untreated (non-mechanized) groups after matching. Overall, the insignificant p-values from the likelihood ratio test, the substantial reduction in total bias, and the low pseudo R^2 values observed after matching across all algorithms (as presented in Table 4.12) indicate that the propensity score specification effectively achieved balance in the distribution of covariates between the treated and untreated groups.

To address this concern, a bounding or sensitivity analysis approach is employed to determine how strongly unobserved factors would need to affect the treatment assignment process to alter the conclusions of the matching analysis (Rosenbaum & Rubin, 1983) (Also see Output 1 in Appendix VI). This approach involves estimating upper and lower bounds using the Wilcoxon signed-rank test to test the null hypothesis of no treatment effect across different hypothetical levels of unobserved selection bias. The absence of hidden bias implies that individuals with similar observed characteristics have an equal likelihood of receiving treatment, corresponding to an odds ratio of one.

Effect of agricultural mechanization on food security

(Household food consumption scores) in Homa Bay County

Table 4-13: Effect of agricultural mechanization on food security (Household Food Consumption Scores)

		Sample size		Mean outcome				
Matching Algorithm	**Livelihood Outcome**	**Treated/ Mechanized**	**Control/ Non-Mechanized**	**Treated/ Mechanized**	**Control/ Non-Mechanized**	**ATT**	**Standard error**	**t-Statistics**
Nearest neighbor matching (3)	Household Food Consumption Scores	357	113	56.38	47.11	9.17	3.05	3.00***
Kernel Matching	Household Food Consumption Scores	357	113	56.27	46.79	9.47	2.82	3.36***

Note: *, ** and *** denote significant at 10%, 5%, and 1% levels, respectively; t-values are calculated using bootstrap with 50 replications.

The results illustrating the impact of agricultural mechanization on household food security, measured using the FCS, based on the KM and Three NNM methods, are presented in Table 4.9. Based on 50 bootstrap replications conducted to test statistical significance, the findings from both matching methods demonstrate that agricultural mechanization exerts a positive and significant impact on the HFCS.

Under the three NNM approach, mechanization positively influenced HFCS, with the effect being statistically significant at the 1% level. Similarly, the KM method produced a positive and statistically significant relationship between mechanization and HFCS at the 1% level, as presented in Table 4.9. The ATT column represents the mean difference in HFCS between the treated group (mechanized cereal farmers) and the control group (non-mechanized cereal farmers). The positive ATT values indicate that, on average, mechanized farmers achieved higher food consumption scores, reflecting better household food security outcomes compared to their non-mechanized counterparts. The estimated effect of agricultural mechanization on the HFCS ranged from 46.79 to 56.38. This indicates that mechanized cereal farming households in Homa Bay County had higher HFCS values compared to non-mechanized households, reflecting more frequent and diverse food consumption. Therefore, mechanized farmers exhibited higher levels of household food security than their non-mechanized counterparts.

4.4.3 Qualitative Analysis from Respondents

Triangulation was conducted to integrate and validate findings from both quantitative and qualitative data sources. This process involved synthesizing results from the household survey, FGDs, and KIIs with ward agricultural officers and selected cereal farmers. The triangulation helped to enrich understanding of how agricultural mechanization influence food security among cereal producers in Homa Bay County.

The quantitative findings revealed that mechanization significantly enhanced household food consumption scores (HFCS), suggesting improved food availability and dietary diversity among mechanized households. These results were corroborated by qualitative evidence from FGDs and KIIs, which emphasized the transformative role of mechanization in improving productivity, timeliness, and income. Farmers repeatedly underscored that the use of tractors and other mechanized tools enabled timely land preparation, which was previously constrained by labor shortages and erratic rainfall.

One farmer from Karachuonyo remarked:

> *Before tractors came to our area, it used to take us weeks to prepare land by hand. By the time we planted, the rains would be almost gone. Now we can prepare several acres within a few days and plant early, which gives us better harvests and more food for the family.*

Agricultural officers echoed similar sentiments, emphasizing the efficiency and yield-enhancing effect of mechanization.

A ward agricultural officer from Rangwe noted:

> *Mechanization has reduced drudgery and improved efficiency in land preparation and planting. Farmers who mechanize often report better yields and even sell surplus maize, which translates into better food and income security.*

These qualitative insights reinforce the statistical finding that mechanization positively affects household food security. Mechanization was perceived not only as a productivity enhancer but also as a driver of agricultural transformation through income diversification, reduced labor dependency, and greater resilience against climate variability.

4.5 Effect of Innovative Agricultural Information Technologies on Food Security in Homa Bay County

This sub-section presents the results and findings of objective 2, including descriptive analysis, inferential analysis of ordered logit regression as well as qualitative findings from respondents.

4.5.1 Descriptive Analysis

Table 4-14: Description of farmers' awareness and adoption of innovative digital agricultural information technologies (DAITs)

Variables	Description	N	Percent
Mbegu Choice	Not Aware	405	85.62
	Moderately aware	56	11.84
	Very Aware	12	2.54
Hello Tractor	Not Aware	407	86.05
	Moderately aware	55	11.63
	Very aware	11	2.33
DigiFarm	Not Aware	401	84.78
	Moderately aware	51	10.78

	Very Aware	21	4.44
Soko Yetu	Not Aware	420	88.79
	Moderately aware	43	9.09
	Very Aware	10	2.11
My Fugo	Not Aware	416	87.95
	Moderately aware	48	10.15
	Very Aware	9	1.9
Mkulima Young	Not Aware	420	88.79
	Moderately aware	46	9.73
	Very Aware	7	1.48
Farm Kenya	Not Aware	423	89.43
	Moderately aware	44	9.3
	Very Aware	6	1.27
Radio	Not Aware	184	38.9
	Moderately aware	164	34.67
	Very Aware	125	26.43
Social Media/internet	Not Aware	278	58.77
	Moderately aware	139	29.39
	Very Aware	56	11.84

The findings indicate that awareness of most digital agricultural information technologies (DAITs) was generally low, with over 80% of farmers unaware of platforms such as Hello Tractor, DigiFarm, Soko Yetu, and Farm Kenya. This suggests that formal digital platforms have limited reach among smallholder farmers, potentially constraining their ability to access timely agricultural information, markets, and services (Table 4.14). In contrast, awareness was relatively higher for more traditional and widely accessible channels, with radio (61.1%) and social media/internet sources (41.23%) being more commonly recognized. This pattern highlights a clear divide between conventional information channels and newer digital platforms. Farmers appear to rely more on familiar and accessible sources, particularly radio, which does not require advanced digital skills or infrastructure. Qualitative findings reinforce this observation, with one farmer stating: *"We mostly get farming information from the radio because it is easy to access and understand."* Another participant added: *"These apps you mention, many of us have never heard of them or don't know how to use them."* The low awareness of formal digital platforms points to potential barriers such as limited digital literacy, inadequate sensitization, and restricted access to smartphones or internet services. As noted by a key informant: *"There are many digital tools available, but farmers are not fully aware of them, and training is still limited."* The findings suggest that while information access exists, it is skewed toward traditional channels, with limited penetration of specialized digital agricultural platforms among cereal farmers.

Table 4-15: Farmers' adoption of DAITs in the last production cycle (%)

Variables	Description	N	Percent/mean
Mbegu Choice	No	47	69.12
	Yes	21	30.88
Hello Tractor	No	450	95.14
	Yes	23	4.86
DigiFarm	No	440	93.02
	Yes	33	6.98
Soko Yetu	No	455	96.19
	Yes	18	3.81
My Fugo	No	452	95.56
	Yes	21	4.44
Mkulima Young	No	455	96.19
	Yes	18	3.81
Farm Kenya	No	457	96.62
	Yes	16	3.38
Radio	No	277	58.56
	Yes	196	41.44
Social Media/internet	No	376	79.49
	Yes	97	20.51
Average number of DAITs adopted by farmers		473	1
Percent of farmers adopting at least one of DAITs in their farm	No	240	50.74
	Yes	233	49.26

The findings show that adoption and use of digital agricultural information technologies (DAITs) were generally low, with fewer than 10% of farmers using most platforms. An exception was Mbegu Choice, which recorded relatively higher uptake (30.88%), suggesting that platforms offering direct and practical value (e.g., seed information) may have better acceptance among farmers. In contrast, radio (41.44%) and social media/internet (20.51%) remained the most commonly used sources of agricultural information, reinforcing the continued dominance of more accessible and familiar communication channels. Overall, 49.26% of respondents had adopted at least one DAIT, with an average adoption of one technology per farmer, indicating low intensity of use. This suggests that even among adopters, engagement with digital technologies is limited rather than diversified. Farmers tend to rely on a single, familiar source rather than integrating multiple platforms into their farming activities. As one farmer explained during FGDs: *"I only use one platform because it is what I understand; using many is difficult."* Qualitative findings further indicate that adoption is influenced by ease of use, perceived relevance, and access to devices or internet connectivity. Some farmers expressed challenges in navigating digital platforms: *"These applications need training; without it, many farmers cannot use them effectively."* Key informants also noted that limited awareness and technical support reduce uptake: *"Adoption is still low because farmers are not adequately trained and some lack smartphones or reliable network coverage."* The results indicate that while nearly half of the farmers have been exposed to at least one digital tool, actual usage remains shallow and concentrated in a few accessible platforms, reflecting constraints related to skills, access, and perceived usefulness.

4.5.2 Inferential Analysis

Diagnostic tests for the ordered logistic regression showed no multicollinearity among explanatory variables (mean VIF = 1.37), indicating that the model satisfied the non-collinearity assumption (See output 2 in Appendix VI). The link test and Ramsey RESET test confirmed that the regression was well specified, with no evidence of major functional form errors or omitted key variables ($p > 0.05$). Although heteroskedasticity and some non-normality were detected, the use of maximum likelihood estimation with robust standard errors ensured that the model estimates remained reliable and valid

Table 4-16: Ordered logit regression

	Coefficients (log-odds)	**Standard errors**	**z-values**	**P>z**
Variables				
Adoption of at least one of the DAITs in the farm (0=No, 1=Yes)	0.96	0.20	4.73	0.00***
Gender of the respondent (0=Female, 1=Male)	0.35	0.20	1.78	0.07*
Marital status of the respondent (0=Not married, 1=Married)	-0.12	0.26	-0.44	0.66
Age of the respondent (1=18-35 years, 2=36-49 years, 3=Above 49 years)	-0.09	0.17	-0.55	0.58
Education of the respondent (1=No education, 2=Adult education, 2=Primary, 3=Secondary, 4=Tertiary (College and universities))	0.20	0.11	1.79	0.07*
Household size	0.01	0.03	0.43	0.67
Years of farming experience	0.04	0.01	3.84	0.00***

Ownership of livestock (0=No, 1=Yes)	0.26	0.21	1.25	0.21
Main occupation of respondent (0=Non-farming, 1=Farming)	-1.59	0.26	-6.07	0.00***
Total household income (KES)	0.00	0.00	3.46	0.00***
Access to credit (0=No, 1=Yes)	0.37	0.20	1.85	0.07*
Access to market (0=No, 1=Yes	-0.18	0.30	-0.61	0.54
Access extension services (0=No, 1=Yes)	0.33	0.22	1.47	0.14
/cut1	0.17	0.70		
/cut2	1.26	0.70		
/cut3	2.26	0.70		

Note: Number of observations = 473; LR chi square (13) = 156.95; Prob > chi2 = 0.0000; Log likelihood = -542.92098; Pseudo R squared = 0.1263

The ordered logistic regression model assessing the impact of DAIT uptake and socio-economic factors on food security was statistically significant overall (LR $\chi^2 = 156.95$, $p < 0.001$), indicating that at least one predictor meaningfully influences food security status among the 473 cereal farmers (Table 4.16). The model's pseudo-R^2 of 0.1263 suggests that about 12.6% of the variation in food security (measured by FIES categories) is explained by the included variables, which is acceptable for cross-sectional behavioural data. Overall, the results indicate a good model fit and confirm that adoption of DAITs, extension services access, markets access and, income, and other demographic factors are relevant determinants of food security among farmers in Homa Bay County.

The adoption of at least one digital agricultural information technology (DAIT) had a positive and statistically significant effect on household food security ($\beta = 0.9566$, $p < 0.01$). This indicates that farmers who adopted at least one DAIT were more likely to fall into higher food security categories compared to non-adopters. This pattern suggests that access to timely information such as input availability, market prices, and weather updates may enhance decision-making and improve household food outcomes. Qualitative evidence supports this, with one farmer noting: *"When I get information on when to plant or where to sell, it helps me avoid losses and have enough food."*

Gender had a positive but weakly significant effect on food security ($\beta = 0.3517$, $p = 0.074$), suggesting that male-headed households were slightly more likely to experience higher food security levels. Education was positively associated with food security and was significant at the 10% level ($\beta = 0.202$, $p = 0.073$).

Farming experience showed a positive and highly significant relationship with food security ($\beta = 0.0401$, $p < 0.01$), suggesting that households with more years of farming were more likely to achieve higher levels of food security. In contrast, the main occupation variable had a negative and statistically significant effect ($\beta = -1.586$, $p < 0.01$), indicating that households relying primarily on farming as their main livelihood were less likely to be food secure. Household income was found to have a positive and significant influence on food security ($\beta = 3.20e-06$, $p = 0.001$), while access to credit also showed a positive, though marginally significant, effect ($\beta = 0.366$, $p = 0.065$). Overall, the findings highlight that adoption of Digital Agricultural Information Technologies (DAITs), farming experience, and higher household income were the most important positive determinants of food security among cereal-producing households in Homa Bay County.

4.5.3 Qualitative Analysis from Respondents

Triangulation was conducted to integrate and validate findings from both quantitative and qualitative data sources. This process involved synthesizing results from the household survey, FGDs, and KIIs with ward agricultural officers and selected cereal farmers. The triangulation helped to enrich understanding of how innovative agricultural information technologies influence food security among cereal farmers in Homa Bay County. The integration of digital agricultural information systems was another key theme emerging from FGDs and KIIs. Qualitative data revealed their growing influence on decision-making, market access, and food security outcomes.

A young farmer from Suba North explained how digital tools enhanced their farming efficiency:

> *Nowadays, we don't wait for officers to visit us physically. We get advice on planting dates, pest control, and fertilizer use through WhatsApp groups and radio programs. This helps us plan better and avoid losses.*

Similarly, an agricultural extension officer emphasized the value of digital information dissemination in bridging knowledge gaps:

> *Digital platforms have made extension work easier. Through SMS alerts and mobile applications, farmers receive timely weather updates and input market prices, which helps them make informed decisions that improve production and income.*

These narratives highlight how digital agricultural information technologies complement mechanization by improving access to real-time information, optimizing production decisions, and enhancing market participation, all of which contribute to improved household food security. The findings are consistent with secondary evidence showing that digital innovations strengthen agricultural resilience by reducing information asymmetry and promoting efficient resource use.

4.6 Effect of SAPs and Food Security in Homa Bay County

This sub-section presents the results and findings of objective 3, including descriptive analysis, inferential analysis of poison regression as well as qualitative findings from respondents.

4.6.1 Descriptive Analysis

The findings indicate that awareness of sustainable agricultural practices (SAPs) was generally low, with 61.95% of farmers reporting no awareness and only 8.88% indicating high awareness. This suggests that knowledge of environmentally sustainable farming methods is still limited among most cereal farmers, which may constrain the transition toward climate-resilient agriculture. Information on SAPs was mainly obtained through informal and semi-formal channels, particularly fellow farmers (33.33%), private/NGO extension officers (31.67%), and social or mass media (24.44%), indicating that peer learning and external development actors play a key role in knowledge dissemination. Qualitative findings further highlight the importance of informal networks in knowledge transfer. One farmer noted: *"We mostly learn these practices from neighbours or NGO officers who come to train us."* This suggests that formal extension systems are not the dominant source of SAP knowledge, potentially limiting the consistency and depth of information received by farmers.

In terms of capacity, 78.33% of farmers reported only basic knowledge of SAPs, and 67.22% indicated they had received only basic training, although a large proportion (78.33%) perceived SAPs as easy to use. This indicates a gap between perceived usability and actual depth of understanding, suggesting that farmers may adopt practices without fully understanding their long-term benefits or technical requirements.

Adoption levels of SAPs were relatively low. The most commonly practiced methods were crop rotation (31.08%), intercropping (23.89%), and minimal tillage (21.99%), while more comprehensive adoption remained limited, with only 25.52% of households adopting at least three SAPs and an average adoption of one SAP per farmer. This pattern suggests that SAP adoption is selective and fragmented rather than holistic, often influenced by practicality, cost, and labour considerations. As one farmer explained: *"We choose the practices that are easier and cheaper to apply, like intercropping and rotation."* The findings show that while SAPs are present in the study area, low awareness, limited training, and partial adoption constrain their widespread and integrated use, potentially limiting their full contribution to long-term agricultural sustainability.

Table 4-17: Description of farmers' awareness, knowledge, and adoption of SAPs

Variables	Description	N	%
Level of awareness of sustainable agricultural practices (SAPs)	Not aware	293	61.95
	Moderately aware	138	29.18
	Very aware	42	8.88
How respondent first learned about the SAPs	Private/NGO extension officers	57	31.67
	Government extension officers	11	6.11
	Cooperative/farmer groups	7	3.89
	Fellow farmers/Relatives/neighbors	60	33.33
	Social media/TV/radio/internet	44	24.44
	School/colleges/learning institutions	1	0.56
Respondents' rating of their level of knowledge of SAPs	None	13	7.22
	Basic knowledge	141	78.33
	Moderately knowledgeable	16	8.89
	Very knowledgeable	10	5.56
Respondents' rating of their level of training received on SAPs	No training	46	25.56
	Basic training	121	67.22
	Modest training	10	5.56
	Extensive training	3	1.67
Adoption of different SAPs in the last production year	Minimal tillage	104	21.99
	Crop rotation	147	31.08
	Mulching	47	9.94
	Intercropping	113	23.89
	Cover cropping	84	17.76
	Agroforestry	48	10.15
	Crop diversification/mixed cropping	47	9.94
	Inorganic fertilizer application	5	1.06
	Water conservation techniques (drip irrigation)	3	0.63
	Regenerative agriculture	12	2.54
	Renewable energy sources (solar-powered irrigation)	1	0.21

4.6.2 Inferential Analysis

Multicollinearity was not a concern with mean VIF = 1.37 and the link test showed no evidence of model misspecification, indicating that the Poisson regression model was correctly specified and the explanatory variables were appropriately independent (See Output 3 in Appendix VI). The improved log-likelihood values indicated that the Poisson model fits the data well and is suitable for analyzing determinants of household dietary diversity.

Table 4-18: Poisson regression

Variables	Coefficient	Robust Standard Error	z	P>z
Adoption of at least three sustainable agricultural practices (SAPs) (0=No, 1=Yes)	0.14	0.04	3.85	0.00***
Gender of the respondent (0=Female, 1=Male)	0.04	0.03	1.35	0.18
Marital status of the respondent (0=Not married, 1=Married)	0.09	0.04	2.01	0.05**
Age of the respondent (1=18-35 years, 2=36-49 years, 3=Above 49 years)	0.01	0.03	0.41	0.68
Education of the respondent (1=No education, 2=Adult education, 2=Primary, 3=Secondary, 4=Tertiary (College and universities))	0.04	0.02	2.14	0.03**
Household size	-0.02	0.01	-2.31	0.02**
Years of farming experience	0.00	0.00	2.16	0.03**
Ownership of livestock (0=No, 1=Yes)	0.10	0.03	2.96	0.00***
Main occupation of respondent (0=Non-farming, 1=Farming)	-0.01	0.04	-0.37	0.71
Total household income (KES)	0.00	0.00	3.68	0.00***
Access to credit (0=No, 1=Yes)	0.03	0.03	1.14	0.25
Access to market (0=No, 1=Yes)	0.18	0.06	2.98	0.00
Access extension services (0=No, 1=Yes)	0.10	0.04	2.56	0.01
Constant	1.36	0.11	12.51	0.00

Note: Number of observations = 431; Wald $chi^2(13)$ = 130.22; Prob > chi square =0.0000; Log pseudolikelihood = -957.83969; Pseudo R^2 = 0.0471; ***, ** and * denote significant at 1%, 5% and 10% levels, respectively

The Poisson regression model was statistically significant overall (Wald $\chi^2 = 130.22$, $p < 0.001$), indicating that the explanatory variables collectively influence household dietary diversity, despite a modest pseudo R^2 of 0.0471 typical of count data models. The model's log pseudolikelihood was –957.84, and the results confirm that the model provides meaningful explanatory power for analyzing dietary diversity as a proxy for food security..The adoption of at least three sustainable agricultural practices (SAPs) had a positive and statistically significant effect on household dietary diversity ($\beta = 0.14$, $p < 0.01$). This indicates that households adopting multiple SAPs were more likely to have higher dietary diversity than non-adopters.

Marital status had a positive and statistically significant association with dietary diversity ($\beta = 0.09$, $p = 0.05$), suggesting that married households are more likely to consume a wider variety of food groups. This may reflect improved resource pooling and shared decision-making within households. Qualitative responses support this, with one respondent noting: *"When we are two, we plan better for food and can afford different types of food."*

Education level also showed a positive and significant effect ($\beta = 0.04$, $p = 0.03$), indicating that more educated farmers tend to achieve better dietary diversity. This may be linked to improved awareness of nutrition and better use of income and farm outputs for food consumption choices. In contrast, household size had a negative and significant relationship with dietary diversity ($\beta = –0.02$, $p = 0.02$), suggesting that larger households may face increased pressure on available food resources, leading to reduced variety in diets.

Farming experience was positively associated with dietary diversity ($\beta = 0.00$, $p = 0.03$), implying that more experienced farmers are slightly more likely to diversify household diets, possibly due to accumulated knowledge on production and food utilization. Similarly, livestock ownership had a strong positive effect ($\beta = 0.10$, $p < 0.01$), highlighting its role as an important source of diverse foods such as milk, meat, and eggs. One farmer explained: *"Keeping chickens and goats helps us have different foods even when crops fail."*

Household income also had a positive and highly significant influence ($\beta = 0.00$, $p < 0.01$), indicating that higher income improves the ability to purchase a variety of foods beyond own production. In addition, access to markets was positively associated with dietary diversity ($\beta = 0.18$, $p < 0.01$), suggesting that proximity and access to markets enhances food variety through increased availability and affordability of different food groups. Likewise, access to agricultural extension services had a positive and significant effect ($\beta = 0.10$, $p < 0.01$), indicating that advisory services may indirectly improve dietary outcomes through better farming and livelihood decisions. A key informant noted: *"When farmers are trained, they not only improve production but also understand nutrition and food choices."*

The findings show that dietary diversity is shaped by a combination of household structure, human capital, asset ownership, income levels, and access to services, with livestock, markets, and income emerging as particularly strong contributors to improved dietary outcomes among cereal-farming households.

4.6.3 Qualitative Analysis from Respondents

Triangulation was conducted to integrate and validate findings from both quantitative and qualitative data sources. This process involved synthesizing results from the household survey, FGDs, and KIIs with ward agricultural officers and selected cereal farmers. The triangulation helped to enrich understanding of how sustainable agricultural practices collectively influence food security among cereal farmers in Homa Bay County.

The FGDs and KIIs also revealed that SAPs such as soil fertility management, crop rotation, integrated pest management, and conservation tillage play a role to ensure a long-term food security. Farmers who adopted these practices reported improved soil health, reduced input costs and more stable yields. A farmer from Rangwe described the relationship between SAPs and food availability as follows:

> *When we started practicing crop rotation and using compost manure, our maize yields improved. Even in seasons of poor rainfall, the soil still holds moisture, and we do not struggle with hunger like before.*

Ward agricultural officers further noted that sustainability and mechanization are complementary, not competing, strategies. One officer remarked:

> *Mechanization should go hand-in-hand with sustainable land use. If farmers over-plough without conservation, they will degrade the soil. But when mechanization is combined with good soil practices, food security improves in a lasting way.*

This perspective underscores the need for balanced adoption where technological intensification through mechanization is accompanied by environmental stewardship to ensure sustainable productivity. The convergence of quantitative and qualitative findings thus demonstrates that food security is a multidimensional outcome influenced by the interplay between technology adoption, access to agricultural information, and sustainable resource management.

4.7 Overall Model

Objective 1: Probit model

Adoption of mechanization = -0.25 - 0.15Gender of the respondent+0.56Marital status of the respondent-0.15 Age of the respondent-0.01 Education of the respondent (1=No education, 2=Adult education, 2=Primary, 3=Secondary, 4=Tertiary -0.05 Household size +0.02 Years of farming experience+0.42 Ownership of livestock+0.25 Main occupation of respondent+ 0.00Total household income-0.04Access to credit+0.64Access extension services

Objective 2: Ordered regression

DAITs = 0.96 Adoption of at least one of the DAITs in the farm + 0.35 Gender of the respondent-0.12 Marital status of the respondent-0.09 Age of the respondent (1=18-35 years, 2=36-49 years, 3=Above 49 years) +0.20 Education of the respondent + 0.01 Household size+ 0.04 Years of farming experience+0.26 Ownership of livestock-1.59 Main occupation of respondent + 0.00Total household income + 0.37Access to credit- 0.18Access to market+0.33 Access extension services (0=No, 1=Yes)

Objective 3: Poisson regression

Household Dietery Diversity (HDDs) = 1.36 + 0.14 Adoption of at least three sustainable agricultural practices (SAPs)+ 0.04 Gender of the respondent+0.09 Marital status of the respondent + 0.01 Age of the respondent + 0.04 Education of the respondent -0.02 Household size + 0.00 Years of farming experience + 0.10 Ownership of livestock -0.01 Main occupation of respondent + 0.00 Total household income (KES) + 0.03 Access to credit + 0.18 Access to market + 0.10 Access extension services

4.8 Chapter summary

This chapter has presented the study findings and key results. It has outlined the outcomes related to the three specific research objectives and the corresponding research questions that guided the investigation. The chapter integrates both quantitative and qualitative evidence, providing a comprehensive analysis and interpretation of data collected from cereal farmers and agricultural officers in Homa Bay County. The findings are discussed in relation to existing empirical.

CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter provides a discussion of the study findings, followed by the conclusions and recommendations drawn from the results. It also highlights the study's contribution to knowledge, offers policy and practical recommendations, and identifies areas for further research. The conclusions are based on empirical evidence and are aligned with the study objectives and research questions.

5.2 Discussions of Findings

This sub-section presents discussions of the study objectives and research questions.

5.2.1 Agricultural mechanization and food security

The findings indicate a relatively high level of mechanization uptake among cereal farmers in Homa Bay County, with over three-quarters of farmers mechanizing at least one farming activity. However, this adoption is highly selective and stage-specific, concentrating almost exclusively on land preparation, particularly ploughing, while planting, weeding, irrigation, and harvesting remain largely manual or animal-powered. This pattern reflects what can be interpreted as a "partial mechanization trap", where farmers adopt mechanization only where it offers immediate and visible labour savings, but avoid full-system mechanization due to cost, risk, and limited service availability. Land preparation is often the most time-sensitive and labour-intensive stage, making it the most attractive entry point for mechanization, whereas other operations require either higher precision, specialized equipment, or repeated seasonal investment, which smallholders are less able or willing to afford.

The dominance of machinery hiring over ownership further reinforces this interpretation. Rather than signalling lack of interest, it reflects a service-dependent mechanization model constrained by capital limitations, weak credit access, and limited subsidy coverage. In this context, mechanization is not an asset accumulation process but a transactional service accessed when needed. The reported absence or inadequacy of government subsidies exacerbates this dependence, limiting farmers' ability to transition from occasional use to sustained mechanization systems. Crop-specific patterns also support this explanation, as tractors dominate across maize, sorghum, rice, and millet production, while animal traction remains a fallback technology for resource-constrained households. The very low use of harvesting equipment points to a structural gap in post-harvest mechanization, which may perpetuate labour bottlenecks, increase post-harvest losses, and weaken the overall productivity gains expected from mechanization investments.

The statistically significant differences in food consumption scores between mechanized and non-mechanized farmers suggest that even this partial mechanization has meaningful welfare effects. Mechanized households show improved food security outcomes, likely through higher productivity, improved timeliness of operations, and increased income generation. However, the fact that mechanization is concentrated at the land preparation stage raises an important nuance: the observed food security gains may be driven more by timing efficiency and labour substitution in early production stages than by full productivity transformation across the agricultural cycle. This partially explains why mechanization improves food access but may not yet translate into optimal system-wide efficiency. These findings align with Molosiwa (2019), who reported that mechanization improves food availability and dietary diversity through improved efficiency in land preparation and timely planting in Botswana. In the context of Homa Bay County, mechanization therefore appears to function as a selective productivity enhancer rather than a comprehensive transformation tool.

The probit results further deepen this interpretation by showing that mechanization adoption is shaped more by economic capacity and institutional access than by demographic characteristics. The positive effect of marital status suggests that household stability and pooled decision-making enhance the ability to access mechanization services, consistent with Fadeyi et al. (2022). The negative effect of household size reflects a substitution effect, where abundant family labour reduces the need for mechanized services, consistent with Kassie et al. (2015). Farming experience increases adoption likelihood, supporting Manda et al. (2016), as experienced farmers are better able to evaluate the cost-benefit trade-offs of mechanization under uncertainty.

Livestock ownership and household income emerge as reinforcing economic enablers, indicating that mechanization is closely tied to asset-based resilience and liquidity capacity, consistent with Axman (2021) and Mohammed et al. (2023). Access to extension services is the strongest institutional determinant, highlighting that adoption is not purely financial but also informational. Farmers exposed to extension services are more likely to understand the benefits and operational requirements of mechanization, consistent with Mwangi and Kariuki (2015). This underscores that mechanization uptake is simultaneously a knowledge and capital constrained process, rather than a purely economic decision.

Overall, the findings suggest that mechanization in Homa Bay County is not a uniform technological transition but a gradual and uneven adaptation process shaped by cost constraints, labour availability, and institutional support structures. Strengthening extension systems, improving affordability of mechanization services, and expanding post-harvest mechanization could therefore shift current partial adoption toward more integrated and productivity-enhancing mechanization systems.

The positive effect of mechanization on household food consumption scores further reinforces this interpretation. Mechanization improves agricultural efficiency by enabling timely land preparation, planting, and harvesting, which enhances yields and reduces production risks. These gains translate into improved household income and better access to diverse foods. However, the benefits appear to be incremental rather than transformative, given the limited mechanization of later production stages. Mechanization also reduces labour burdens, freeing household labour for other income-generating activities, thereby strengthening resilience. These findings are consistent with Mohammed et al. (2023), who reported that mechanization improves household welfare and food security through enhanced productivity and efficient resource utilization. In Homa Bay County, mechanization should therefore be understood as a critical but incomplete pathway to food security, whose full potential remains constrained by structural and institutional limitations..

5.2.2 Innovative agricultural information technologies and food security

The findings reveal a substantial gap between awareness and actual uptake of digital agricultural information technologies (DAITs) among farmers in Homa Bay County. While traditional information channels such as radio and, to a lesser extent, social media are relatively well recognized and utilized, awareness and use of specialized digital agricultural platforms remain extremely low. Beyond individual-level factors such as digital literacy and extension exposure, this pattern reflects deeper structural constraints within the rural digital ecosystem. In particular, limited access to reliable internet connectivity, inadequate electricity supply in some rural areas, and the high cost of smartphones and data services significantly restrict farmers' ability to consistently engage with DAITs. These infrastructural barriers mean that even where awareness exists, sustained usage is often not feasible, reinforcing dependence on low-cost and offline channels such as radio.

Additionally, weak digital infrastructure is compounded by institutional and content-related limitations. Many digital platforms are not sufficiently localized or embedded within routine extension systems, reducing their perceived relevance and trustworthiness among farmers. This explains why radio remains dominant, as it is not only accessible but also stable and culturally embedded within rural information systems. Although social media and internet-based platforms show moderate awareness and adoption, their use remains highly uneven, largely limited to farmers with better connectivity, smartphone access, and digital skills. This suggests that DAIT adoption is shaped not only by individual readiness but also by unequal access to enabling infrastructure and services, reinforcing a broader digital divide in rural agriculture. Strengthening digital extension services, improving rural electrification, reducing data costs, and expanding mobile network coverage are therefore critical prerequisites for meaningful DAIT uptake. Increased integration of DAITs into public extension systems could also enhance trust and usability by embedding them within familiar institutional structures.

The positive and significant effect of DAIT adoption on food security, as shown by the ordered logistic regression, highlights the potential of digital technologies to enhance household welfare among cereal farmers. DAITs improve access to timely production and market information, reduce transaction costs, and enhance decision-making efficiency, collectively contributing to improved food availability and stability. However, these benefits are unevenly distributed, as they are contingent on underlying infrastructure and access conditions. These findings are consistent with Makine et al. (2018) in Kenya and Ngwilizi et al. (2022) in Tanzania, who reported that digital agricultural platforms significantly improve productivity, income, and dietary diversity among smallholder farmers.

The weak but positive influence of gender suggests that male-headed households may still have a slight advantage in food security, possibly due to better access to productive resources such as land, credit, and digital tools. However, the marginal significance implies narrowing gender disparities, potentially reflecting increasing inclusion of women in agricultural and digital empowerment initiatives. Education was found to have a positive association with food security, indicating that educated farmers are better positioned to navigate both agricultural and digital information systems. This finding supports Meiguran and Basweti (2016), who emphasized the role of education in improving farm management and household welfare. Farming experience emerged as a highly significant determinant of food security, suggesting that experienced farmers possess better knowledge of agro-ecological conditions and risk management strategies, consistent with Nyabuto (2022).

The negative effect of farming as the main occupation underscores the importance of livelihood diversification. Households relying solely on agriculture remain more exposed to climatic, market, and input-related shocks, while non-farm income provides a buffer that enhances food access, consistent with Owuor et al. (2020). The positive impact of household income further confirms its central role in enabling food purchases and investment in productivity-enhancing technologies. Similarly, access to credit improves food security by facilitating timely acquisition of inputs and adoption of improved technologies, as reported by Khan and Kim (2025).

Overall, the discussion highlights that while DAITs have strong potential to improve food security, their effectiveness is constrained by structural barriers such as inadequate digital infrastructure, limited electricity access, high connectivity costs, and weak institutional embedding. This implies that technological adoption alone is insufficient; rather, food security gains depend on addressing the broader enabling environment. Strengthening digital infrastructure, promoting inclusive access, and integrating DAITs within extension systems are therefore essential for maximizing their impact alongside livelihood diversification and improved financial access.

5.2.3 SAPs and food security

The results indicate generally low awareness of sustainable agricultural practices (SAPs) among farmers in the study area, highlighting a persistent information and capacity gap. This finding is consistent with previous studies in rural Kenya and other parts of Sub-Saharan Africa, which identify limited awareness and information access as key constraints to SAP adoption (Kassie et al., 2015; Kanyenji et al., 2022). However, beyond awareness, the low adoption rates observed in this study can also be explained by structural and system-level constraints within agricultural extension delivery. The dominance of informal peer networks and NGO/private actors as primary information sources suggests that public extension systems are not sufficiently present, coordinated, or trusted to deliver sustained and technically detailed guidance on SAPs. As a result, farmers often receive fragmented or inconsistent information, which limits their ability to adopt and integrate multiple practices.

Although most farmers reported basic awareness and knowledge of SAPs, the limited proportion receiving advanced or continuous training indicates that extension engagement is largely episodic rather than transformative. This helps explain why awareness has not translated into deep adoption. While SAPs are perceived as easy to use, ease of use alone is insufficient to drive uptake when farmers lack sustained technical support, demonstration exposure, and follow-up guidance. In addition, adoption remains low because SAPs are typically knowledge-intensive and management-dependent practices that require continuous learning, experimentation, and adaptation to local agro-ecological conditions. Without strong extension reinforcement, farmers tend to adopt only isolated practices rather than integrated packages.

The observed preference for crop rotation, intercropping, and minimal tillage reflects a rational selection of low-cost, low-risk practices that fit within existing labour and resource constraints. However, the limited adoption of multiple SAPs suggests weak system integration and highlights the absence of coordinated advisory support that promotes bundled or complementary practices. Similar patterns have been reported in Sub-Saharan Africa, where SAP adoption is constrained not only by awareness but also by weak extension intensity, limited training continuity, and inadequate institutional follow-up (Kassie et al., 2015; Mango et al., 2018).

From a systems perspective, these findings imply that improving SAP adoption requires restructuring extension services from information dissemination units into continuous learning and innovation support systems. This includes strengthening field-based demonstration farms, promoting farmer field schools, and shifting toward bundled advisory packages that integrate soil fertility management, conservation agriculture, and climate-smart practices rather than promoting isolated interventions. Additionally, embedding SAP training within existing farmer groups and cooperatives could enhance peer learning while improving consistency and reach. Strengthening coordination between public extension services and NGO actors would also reduce fragmentation and improve message coherence.

The positive and significant effect of adopting multiple SAPs on dietary diversity (Poisson regression results) underscores the importance of integrated farming systems in improving household nutrition. Practices such as crop rotation, organic manure use, conservation tillage, and intercropping enhance soil fertility, stabilize yields, and diversify production, thereby improving access to a wider range of foods. This finding is consistent with Kassie et al. (2015) and Ng'endo et al. (2021), who reported that SAP adoption improves food security through productivity and diversification pathways.

Marital status positively influences dietary diversity, suggesting that household cooperation and pooled resources improve food access decisions, consistent with Mango et al. (2018). Education plays a critical role in enhancing dietary outcomes, indicating that informed farmers are better able to integrate agricultural and nutritional knowledge into household consumption decisions, consistent with Chege et al. (2015). Conversely, larger household size reduces dietary diversity, reflecting intra-household resource constraints, consistent with Chagomoka et al. (2016) and Mango et al. (2018). Farming experience enhances dietary diversity by improving production stability and risk management (Ndoro et al., 2020), while livestock ownership strengthens food access through direct consumption and income effects.

Household income remains a key determinant of dietary diversity, as it enables market purchases that complement own production, consistent with Ogutu et al. (2020) and Sibhatu and Qaim (2017). Access to markets and extension services further enhances dietary outcomes by improving food availability and promoting nutrition-sensitive farming practices, consistent with Mwangi et al. (2022) and Kassie et al. (2015).

Overall, the findings suggest that improving SAP adoption requires more than awareness creation; it demands a re-engineering of extension systems toward continuous, bundled, and participatory learning models, supported by stronger institutional coordination and integration with farmer organizations. This would enhance both the depth of adoption and the nutritional benefits of sustainable agricultural practices in rural farming systems.

5.3 Conclusions

From objective one, the study concludes that agricultural mechanization is a critical but uneven driver of food security among cereal farmers in Homa Bay County. While mechanized households recorded improved food consumption outcomes due to higher productivity and income gains, the benefits of mechanization are largely concentrated in specific farm operations (particularly land preparation). This suggests that mechanization is still at a transitional stage, shaped not only by economic capacity but also by structural constraints such as access to services, labour substitution patterns, and institutional support. The findings therefore imply that mechanization alone is not sufficient unless accompanied by improved access, affordability, and extension support that ensures equitable uptake across farming activities.

From objective two, the study concludes that Digital Agricultural Information Technologies (DAITs) contribute meaningfully to food security, but their impact is mediated by inequality in access and digital capacity. While DAITs enhance access to information, market linkages, and climate-related advisory services, their effectiveness depends heavily on farmers' education, income levels, and prior experience. This indicates a growing digital divide in agriculture, where benefits are concentrated among more resourced and informed farmers. The findings suggest that digital transformation in agriculture must go beyond availability of platforms to include targeted capacity building, improved connectivity, and inclusive access strategies to ensure broad-based impact.

From objective three, the study concludes that sustainable agricultural practices (SAPs) are essential for long-term food system resilience, but their adoption remains fragmented and shallow. Although SAPs improve soil fertility, productivity, and dietary diversity, most farmers adopt only a limited number of practices, reflecting constraints in awareness, training, and institutional support. This indicates that sustainability outcomes are currently incremental rather than systemic. The results therefore suggest that strengthening extension systems and integrating SAPs with other agricultural innovations is necessary to achieve sustained productivity gains.

Overall, the study identifies three interconnected pathways through which agricultural interventions influence food security. First, mechanization improves productivity and income but is constrained by structural access and affordability barriers. Second, digital agricultural technologies enhance information access and decision-making, but their benefits are uneven due to disparities in digital literacy and resources. Third, sustainable agricultural practices provide long-term ecological stability, yet their impact is limited by low intensity of adoption. Collectively, these pathways demonstrate that food security in Homa Bay County is not driven by a single intervention, but by the interaction between technology, information access, institutional support, and resource endowment. This highlights the need for an integrated policy approach that simultaneously strengthens mechanization systems, digital inclusion, and sustainable farming transitions.

5.4 Contribution to Knowledge

This study provides new empirical evidence on the determinants and effects of agricultural mechanization, digital agricultural information technologies (DAITs), and sustainable agricultural practices (SAPs) on household food security among cereal farmers in Homa Bay County, Kenya. By employing the HFCS, HFIES and HDDs approach, which remains underexplored in Kenya's smallholder context, the study adds to both practical and theoretical understanding in several ways.

It establishes that agricultural mechanization significantly enhances household dietary diversity and food security outcomes, confirming that institutional and economic factors are stronger determinants of mechanization adoption than demographic factors. The study also demonstrates that the uptake of digital farm information technologies ensures food security by enhancing farmers' access to real-time information, resource-use efficiency, and market opportunities. It further reveals that farmer experience, education, and income diversification strengthen the capacity to leverage digital tools effectively, offering new insights into technology-driven agricultural transformation in rural Kenya. The research too provides empirical confirmation that SAPs contribute positively to household food security by improving soil health, productivity, and dietary diversity. It underscores the importance of institutional support mechanisms and socioeconomic characteristics in shaping sustainable farming adoption and outcomes. Therefore, the study advances existing knowledge by illustrating how the integration of mechanization, digital innovation and sustainability forms a synergistic pathway for achieving resilient and food-secure smallholder farming systems in Kenya contexts.

5.5 Recommendations

5.5.1 Policy Recommendations

Based on the study findings, three key priority policy actions are recommended to improve food security outcomes in Homa Bay County:

i. Scale up affordable mechanization access through service-based models (Highest priority): The government should prioritize the expansion of subsidized Agricultural Mechanization Service Centers (AMSCs) and support private-sector machinery hire services. Given that most farmers currently hire rather than own machinery, a service-based model is more realistic and inclusive than ownership-driven approaches. Policies should focus on reducing service costs and improving geographic coverage in underserved areas.

ii. Strengthen integrated extension systems (High priority): Extension services should be restructured to deliver integrated advisory support combining mechanization, digital agriculture, sustainable practices, and basic nutrition guidance. Rather than fragmented messaging, extension officers should be trained to provide bundled, practical support that directly links production decisions to food security outcomes.

Invest in rural digital infrastructure and inclusion (High priority): Government and development partners should prioritize last-mile digital connectivity and affordability of mobile internet services. Without addressing infrastructure gaps and digital literacy, DAITs will continue to benefit only a small segment of farmers. Investments should therefore focus on both access and usability.

5.5.2 Research Recommendations

i. Longitudinal impact studies: Future research should move beyond cross-sectional analysis to examine long-term causal effects of mechanization, DAITs, and SAPs on food security and resilience outcomes.

ii. Inclusion and inequality-focused studies: Further studies should investigate gender, youth, and income-based disparities in adoption of agricultural innovations, particularly digital tools and mechanization services.

iii. Adoption intensity and bundling studies: Research should examine why farmers adopt only single or limited combinations of technologies and assess the productivity and welfare effects of bundled adoption of mechanization, DAITs, and SAPs.

5.5.3 Management Recommendations

i. Strengthen farmer collective action for mechanization access: Farmer cooperatives should be supported to establish or manage shared machinery hiring centers, reducing individual cost burdens and improving efficiency of service delivery.

ii. Enhance practical digital literacy training: Extension agents and NGOs should prioritize hands-on training sessions rather than theoretical awareness campaigns, focusing on real use cases such as market access, weather updates, and sourcing input.
iii. Promote integrated farming practice packages: Rather than promoting SAPs, mechanization, or ICTs separately, farmers should be supported to adopt combined "technology packages" that improve productivity, sustainability, and food security simultaneously.

5.5.4 Governance Recommendations

i. Improve coordination of agricultural support programs: There is need for stronger coordination among government, NGOs, and private sector actors to avoid duplication and ensure alignment of mechanization, digital agriculture, and sustainability initiatives.
ii. Strengthen performance accountability in extension services: Governance systems should introduce monitoring and performance evaluation mechanisms to improve effectiveness, reach, and responsiveness of extension officers.
iii. Enhance farmer participation in program design: Policies and agricultural programs should be more participatory and demand-driven, ensuring that interventions reflect real farmer constraints, especially for women and youth.

5.6 Suggestions for Further Research

Future research should employ longitudinal or panel data to assess the long-term and causal effects of agricultural mechanization, DAITs, and SAPs on household welfare and food security. Incorporating environmental and sustainability dimensions would help assess the broader ecological implications of technology adoption.

5.7 Limitations of the Research

i. The study employed a cross-sectional research design, which limits the ability to establish long-term causal relationships between agricultural mechanization, digital technologies, sustainable agricultural practices, and food security. The findings therefore reflect associations at a single point in time rather than dynamic changes over time.

ii. The study relied on self-reported food security measures (including dietary diversity, food consumption, and food insecurity experience scales). Such measures may be subject to recall bias, social desirability bias, and reporting inaccuracies, as respondents may underreport or overreport food insecurity experiences or food consumption patterns.

iii. Although propensity score matching (PSM) was used to control for observable differences between adopters and non-adopters, unobserved factors such as farmer motivation, attitudes toward innovation, risk preferences, and management ability may still have influenced adoption decisions and outcomes.

iv. The study was conducted among cereal farmers in Homa Bay County only, which limits the generalizability of the findings to other counties or farming systems with different agro-ecological and socio-economic conditions.

Despite these limitations, the study provides valuable empirical insights into the relationship between agricultural technologies, sustainable practices, and household food security among smallholder farmers in the study area.

REFERENCES

ACDI/VOCA. (2017). *Balancing the systems: Making food and market systems work for nutrition.* Agrilinks.

Acidri, J., Machuki, H., & Seaman, J. (2018). *Livelihood Zones & Household Economy Approach (HEA) Survey Report, Homa Bay County, Kenya.* Walker Institute, Evidence for Development.

Adams, B. T. (2013). Farm machinery automation for tillage, planting cultivation, and harvesting. In B. T. Adams (Ed.), *Handbook of farm, dairy and food machinery engineering* (2nd ed.). Academic Press. https://doi.org/10.1016/B978-0-12-385881-8.00004-5

Adu-Baffour, F., Daum, T., & Birner, R. (2019). Can small farms benefit from big companies' initiatives to promote mechanization in Africa? A case study from Zambia. *Food Policy.* Elsevier.

Aker, J. C., & Ksoll, C. (2019). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *World Development, 62*, 17–32.

Aker, J. C., Ghosh, I., & Burrell, J. (2016). The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics, 47*(S1), 35–48.

Altman, M., & Ngandu, S. (2010). Would halving unemployment contribute to improved household food security for men and women? *Agenda: Empowering Women for Gender Equity, 24*, 52–65.

AMA, B. A., & Chando, D. (2021, June 30). *Transforming rural agriculture through technology and innovation.* IFAD.

AO. (2021). *The state of food and agriculture 2021: Making agrifood systems more resilient to shocks and stresses.* Food and Agriculture Organization of the United Nations.

Asenso-Okyere, K. (2012, February 16). *Africa's agricultural productivity must rise.* Development and Cooperation. Retrieved from https://www.dandc.eu/en/article/africas-agricultural-productivity-must-rise

Asfaw, S., & Shiferaw, B. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Journal of Agricultural Economics, 283–295*.

Axman H. 2021. Policy Brief: *The impact of mechanization in smallholder rice production in Nigeria: Promising business cases for rice smallholders for income increasing and climate smart interventions*. Wageningen, The Netherlands: Wageningen University & Research, Agrotechnology & Food Sciences Group.

Ayenew, H. B. (2018, August 8). Production diversification, dietary diversity and consumption seasonality: Panel data evidence from Nigeria. *BMC Public Health.* https://doi.org/10.1186/s12889-018-5887-6

Balineau, G. A. (2021). *Food systems in Africa: Rethinking the role of markets.* Africa Development Forum Series. Agence Française de Développement and The World Bank.

Balineau, G., & Bernath, A. (2018). *Rethinking the role of markets: Food systems in Africa.*

Bambio, Y. (2025). Gender differences in agricultural productivity: Puzzling evidence from West Africa. *World Development, 197*, https://doi.org/10.1016/j.worlddev.2024.106856

Baumüller, H. (2018). The little we know: An exploratory literature review on the utility of mobile phone-enabled services for smallholder farmers. *Journal of International Development, 30*(1), 134–154.

Beattie, B. R., & Taylor, C. R. (1985). *The economics of production.* Wiley.

Bello, S. R. (2012). *Agricultural machinery and mechanization.* Dominion Publishing Services.

Benin, S. (2014). Conclusions and implications for raising and sustaining high agricultural productivity in Africa. In S. Benin (Ed.), *Agricultural productivity in Africa: Trends, patterns, and determinants* (p. 14). Washington, DC: International Food Policy Research Institute (IFPRI).

Binswanger-Mkhize, H. P. (2013). The stunted structural transformation of the Indian economy: Agriculture, manufacturing, and the rural non-farm sector. *Economic & Political Weekly, 48*(26–27), 5–13.

Blom, S. C. (2014). *Capacity development for resilient food systems.* WWW.2020RESILIENCE.IFPRI.INFO, 1–6. Washington, DC.

Boliko, M. C. (2019). *FAO and the situation of food security and nutrition in the world.*

Bougie, R., & Sekaran, U. (2016). *Research methods for business: A skill-building approach* (7th ed.). Wiley.

Bryman, A., & Bell, E. (2015). *Business research methods* (4th ed.). OUP Oxford.

Cafiero, C., Melgar-Quiñonez, H. R., Ballard, T. J., & Kepple, A. W. (2014). Validity and reliability of food security measures. *Annals of the New York Academy of Sciences, 1331*, 230–248.

Carletto, C., Zezza, A., & Banerjee, R. (2013). Towards better measurement of household food security: Harmonizing indicators and the role of household surveys. *Global Food Security, 2*, 30–40.

CCSA. (2021). *How COVID-19 is changing the world: A statistical perspective.*

CGIAR. (2020, June 9). *CGIAR-platform for Big Data in Agriculture.* Retrieved from https://bigdata.cgiar.org/digital-intervention/safaricom-digifarm/

Chagomoka, T., Drescher, A., Glaser, R., Marschner, B., Schlesinger, J., & Nyandoro, G. (2016). Urban and peri-urban agriculture and dietary diversity in Tamale, Ghana. *Food Security, 8*(3), 491–504. https://doi.org/10.1007/s12571-016-0568-z

Chege, C. G. K., Andersson, C. I. M., & Qaim, M. (2015). Impacts of supermarkets on farm household nutrition in Kenya. *World Development, 72*, 394–407. https://doi.org/10.1016/j.worlddev.2015.03.016

Cheikh Mbow, M. V. (2013, October 25). *Agroforestry solutions to address food security and climate change challenges in Africa.* Elsevier.

Chiuri, J. W., King'ori, I. W., & Obara, P. O. (2020, June 2). *The influence of teacher-parent collaborative monitoring of school attendance on pupils' academic performance in Nyahururu Sub-County, Kenya*.

Choptiany, J. M. H., Christen, C., & Amador, C. (2021). The market systems resilience index: A multi-dimensional tool for development practitioners to assess resilience at multiple levels. *Sustainability.*

Coates, J., Swindale, A., & Bilinsky, P. (2007). *Household Food Insecurity Access Scale (HFIAS) for measurement of food access: Indicator guide*. Food and Nutrition Technical Assistance Project. Retrieved from https://www.fantaproject.org/sites/default/files/resources/HFIAS_ENG_v3_Aug07.pdf

Colson, D. (2022, March 30). How does sustainable agriculture promote food security? *Walter Schindler.* Retrieved from https://walterschindler.com/agricultural-sustainability-articles/promoting-food-security/#:~:text=Sustainable%20agriculture%20increases%20food%20availability%2C%20thereby%20improving%20food,and%20increased%20incomes%20for%20farmers%20and%20their%20familie

Committee for the Coordination of Statistical Activities. (2020). *How COVID-19 is changing the world: A statistical perspective.* Retrieved from https://unstats.un.org/unsd/ccsa/documents/covid19-report-ccsa.pdf

Committee on National Education, Division of Behavioral and Social Sciences, & Board, Food and Nutrition; Council, National Research; Institute of Medicine (US). (2013). *Measurements of food insecurity.* Washington, DC: National Academy Press.

Committee on World Food Security. (2014). *Principles for responsible investment in agriculture and food systems.* Retrieved from www.fao.org/cfs

Connelly, C. (2021, October 21). How agriculture benefits from technology. *The Transformative Power of Technology in Agriculture.* 2023 Siglets.

Cooper, D., & Schindler, P. (2003). *Business research methods* (8th ed.). McGraw-Hill Irwin.

Coughlan de Perez, E., van Aalst, M., Choularton, R., van den Hurk, B., Mason, S., Nissan, H., & Schwager, S. (2019). From rain to famine: Assessing the utility of rainfall observations and seasonal forecasts to anticipate food insecurity in East Africa. *Food Security, 11*(1), 57–68.

Daum, T. (2023). Mechanization and sustainable agri-food system transformation. *Agronomy for Sustainable Development.*

Daum, T. A. (2020). Impacts of agricultural mechanization: Evidence from four African countries. *Hohenheim Working Papers on Social and Institutional Change in Agricultural Development.*

Dercon, S. (2009). Risk, poverty, and insurance. In R. Vargas Hill & M. Torero (Eds.), *Innovations in insuring the poor.* 2020 Vision Focus 17.

DeVries, D. J. (2017, June 30). Doubling productivity and incomes of smallholder farmers in Africa. *Farming First.*

Diao, X., Cossar, F., Houssou, N., & Kolavalli, S. (2016). Mechanization in Ghana: Emerging demand, and the search for alternative supply models. *Food Policy, 61*, 109–119.

Diiro, G. M., Muricho, G., & Fatunbi, A. (2021). How does adoption of labor-saving agricultural technologies affect intra-household resource allocations? The case of push-pull technology in Western Kenya. *Food Policy.* Retrieved from https://doi.org/10.1016/j.foodpol.2021.102114

Drammeh, W., Hamid, N., & Rohana, A. J. (2019). Determinants of household food insecurity and its association with child malnutrition in Sub-Saharan Africa: A review of the literature. *Current Research in Nutrition and Food Science, 7*(3), 589–614.

Easterby-Smith, M., Thorpe, R., & Jackson, P. (2012). *Management research* (Illustrated ed.). SAGE Publications.

Fadeyi, O. A., Ariyawardana, A., & Aziz, A. A. (2022). Factors influencing technology adoption among smallholder farmers: A systematic review in Africa. *Journal of Agriculture and Rural Development in the Tropics and Subtropics, 123*(1), 13–30. https://doi.org/10.17170/kobra-202201195569

Fan, S., & Rao, C. (2020). *The role of smallholder farms in a changing world: The role of smallholder farms in food and nutrition security*.

FAO, & AUC. (2018). *Sustainable agricultural mechanization: A framework.* Food and Agriculture Organization & African Union Commission. Retrieved from http://www.fao.org/3/

FAO, IFAD, UNICEF, WFP, & WHO. (2020). *The state of food security and nutrition in the world 2020: Transforming food systems for affordable healthy diets.* FAO. https://doi.org/10.4060/ca9692en

FAO, IFAD, UNICEF, WFP, & WHO. (2022). *The state of food security and nutrition in the world 2022: Repurposing food and agricultural policies to make healthy diets more affordable*. Food and Agriculture Organization.

FAO, IFAD, UNICEF, WFP, & WHO. (2022). *The state of food security and nutrition in the world 2022: Repurposing food and agricultural policies to make healthy diets more affordable.* Food and Agriculture Organization.

FAO, (2015). *The economic lives of smallholder farmers: An analysis based on household data from nine countries.* Food and Agriculture Organization.

FAO, (2017). *The state of food and nutrition security: How close are we to zero hunger?* Food and Agriculture Organization.

FAO, (2018). *The status of agricultural commodity markets.* Food and Agriculture Organization.

FAO, (2020). *The state of food security and nutrition in the world 2020.* Rome: FAO.

FAO, (2021). *The state of food and nutrition security in the world: Transforming food systems for food security, improved nutrition, and affordable healthy diets for all.* Food and Agriculture Organization.

FAO, (2022). *The future of food and agriculture – Drivers and triggers for transformation.* Food and Agriculture Organization. Retrieved from https://doi.org/10.4060/cc0959en

FAO, (2023). *Sustainable agricultural mechanization.* Food and Agriculture Organization. Retrieved from https://www.fao.org/sustainable-agricultural-mechanization/overview/why-mechanization-is-important/en/

farmbizAfrica. (2023). Mbegu Choice app helps farmers easily access certified seeds online. *Mbegu Choice.*

Financial Times. (2024). UN blasts 'shamefully' high hunger levels. Retrieved from https://www.ft.com/content/d909cbe4-5011-4eab-8118-34c649b690b8

Food and Agriculture Organization (FAO). (2010). *Food security statistics.* Retrieved from http://www.fao.org/economic/ess/food-security-statistics/en/

Food and Agriculture Organization (FAO). (2011). *The status of food insecurity in the world.* Food and Agriculture Organization Press.

Food Crops Directorate. (2023). *Overview of food crop production in Kenya.* Nairobi. Retrieved from http://food.agricultureauthority.go.ke/

Fosso Djoumessi, Y. (2022). New trend of agricultural productivity growth in sub-Saharan Africa. *Scientific African, 18*, e01415.

Galvez, E. (2022). *Scaling up inclusive innovations in agri-food chains in Asia and the Pacific.* Food and Agriculture Organization. Retrieved from https://doi.org/10.4060/cb8306en

Garrity, D. P., Akinnifesi, F. K., Ajayi, O. C., Weldesemayat, S. G., Mowo, J. G., Kalinganire, A., ... & Bayala, J. (2010). Evergreen agriculture: A robust approach to sustainable food security in Africa. *Food Security, 2*(3), 197-214.

GFRC. (2022). *The global report on food crises 2022 | In brief.*

Gilbert, G., & Olory, D. (2018). Crop diversification and household food security status: Evidence from rural Benin. *Agriculture and Food Security, 4*(2): 234-245

Gomez y Paloma, S., & Rapsomanikis, L. (2020). *The role of smallholder farms in food and nutrition security*. Cham, Switzerland: Springer Nature Switzerland AG.

Government of Kenya (GOK) (2022). *Agricultural mechanization services: Enhancing food production in Kenya.* Government of Kenya.

Government of Kenya (GoK). (2018). *Eye on the big four: Budget watch for 2018/19 and the medium term*. Retrieved from www.parliament.go.ke/sites/default/files/2018-09/Budget%20Watch%202018.pdf

Government of Kenya. (2019). *Agricultural sector transformation and growth strategy 2019–2029.* Ministry of Agriculture.

Greene, W. (2000). *Econometric Analysis, 4th Edition.* Upper Saddle River, New Jersey: Prentice-Hall.

Greene, W. (2008). *Econometric Analysis, 6th edition.* USA: Prentice-Hall International Inc.

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics (5th ed.)*. McGraw-Hill Education.

Gwada, R. O., Ouko, K. O., Mayaka, Z. O., & Dembele, B. (2020). Determinants of food security among small-scale soybean households in Butere Sub-County, Kenya. *Contemporary Agriculture, 69*(3–4), 90–101.

Hailemariam. (2022). *Food security in Africa: Current efforts and challenges. Strengthening Food Systems in Africa.*

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). Characterizing selection bias using experimental data. *Econometrica, 66*(5), 1017–1098.

Heimduo. (2016). How does agricultural mechanization affect food security? *Heimduo Universal Source of Knowledge.*

IFRI. (2021). *International Food Policy Research Institute Annual Report.*

Ingutia, R., & Sumelius, J. (2022). Determinants of food security status with reference to women farmers in rural Kenya. *Scientific African, 15*, e01044.

International Dietary Data Expansion Project. (2023, March 25). *Building blocks for diet-related food security analysis.* Data4Diets.

International Food Policy Research Institute (IFPRI). (2023). *Food security simulator – Kenya.* https://doi.org/10.7910/DVN/NS1A7V

Jiquan, P., Zhang, Z., & Li, J. (2022). Impact of agricultural mechanization on agricultural production, income, and mechanisms: Evidence from Hubei Province, China. *Frontiers in Environmental Science, 5*(4): 4-19.

Jules, P., & Zareen, B. P. (2014, October 28). Sustainable intensification in agricultural systems. *Animals of Botany.* Retrieved from www.aob.oxfordjournals.org

Justice, T. A., & Jonathan, M. (2018). Differential impacts of conservation agriculture technology options on household income in Sub-Saharan Africa. *Ecological Economics, 51.* https://doi.org/10.1016/j.ecolecon.2018.05.005

KALRO. (2023). *Report on research on crops production.* Kenya Agricultural and Livestock Research Organization. Retrieved from https://www.kalro.org/divisions/crops

Kamau, R., Wambugu, S., & Njagi, T. (2021). Mechanization and smallholder farmers' productivity in Kenya. *African Journal of Agricultural Research, 16*(3), 223–234.

Kanyenji, G. M., Oluoch-Kosura, W., Onyango, C. M., & Ng'ang'a, S. K. (2022). Does the adoption of soil carbon enhancing practices translate to increased farm yields? A case of maize yield from Western Kenya. *Heliyon, 8*(5), e09500. https://doi.org/10.1016/j.heliyon.2022.e09500

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., & Mekuria, M. (2015). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change, 80*(3), 525–540. https://doi.org/10.1016/j.techfore.2012.08.007

Kassie, M., Ndiritu, S. W., & Shiferaw, B. (2012, April 16–18). *Determinants of food security in Kenya: A gender perspective*. Contributed paper presented at the 86th Annual Conference of the Agricultural Economics Society, University of Warwick, United Kingdom.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., & Erenstein, O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy, 42*, 400–411. https://doi.org/10.1016/j.landusepol.2014.08.016.

Kenya Agricultural and Livestock Research Organization (KALRO). (2023). *Mechanization and food security in Kenya: Policy recommendations.*

Kenya National Bureau of Statistics (KNBS). (2021). *Kenya economic survey 2021.* Kenya National Bureau of Statistics.

Kenya National Bureau of Statistics (KNBS). (2023). *Kenya Demographic and Health Survey (KDHS) 2023*. KNBS.

Khan, C. M., & Kim, S. G. (2025). Evaluating the Impact of Agricultural Credit Access on Smallholder Maize Farmers' Productivity in the Northwest Region of Cameroon. *Sustainability, 17*(17), 7574. https://doi.org/10.3390/su17177574

Kiboi, W. K., Mucheru, P. K., Mututho, L. N., Kimiywe, J. O., Chege, P. M., & Negesse, A. A. (2022). Prevalence of household food security in Kenya: A systematic review and meta-analysis. *International Journal of Community Medicine and Public Health, 9*(7), 2998–3006.

Kinyua, J. M., Omondi, P., & Wambua, J. (2020). Sustainable farming practices and food security in Kenya: A case study of smallholder farmers. *African Journal of Agricultural Research, 15*(4), 512–525.

KIPPRA. (2021, July 20). Re-engineering of Galana Kulalu Food Security Project to maximize its potential. *Kenya Institute for Public Policy Research and Analysis.*

Klytchnikova, I. I., Sadler, M. P., Townsend, R., Edmeades, S., Choudhary, V., Hussain, S., ... & Pietrowski, M. S. (2017). *Future of food: Shaping a climate-smart global food system.* World Bank Group.

KNBS Census. (2019). *2019 Kenya population and housing census: Population by county and sub-county.* Retrieved from https://knbs.or.ke

Knoema. (2022). Kenya - Cereal production. *Knoema Data Repository.*

Kothari, C. R. (2018). *Research methodology: Methods and techniques.* New Age International.

Lowder, S. S. (2014). *What do we really know about the number and distribution of farms and family farms in the world?* ESA Working Paper 14–02. Food and Agriculture Organization (FAO), Agricultural Development Economics Division.

Lutz, G., & Jonathan, K. (2020, October). Agriculture's connected future: How technology can yield new growth. *The Future of Connectivity, 56*(7): 456-470

Mac Clay, P., & Fletcher, R. (2019). *Analyzing agribusiness value chains*. *International Food and Agribusiness Management Association*.

Macharia, T. N., Ochola, S., Mutua, M. K., & Kimani-Murage, E. W. (2018). Association between household food security and infant feeding practices in urban informal settlements in Nairobi, Kenya. *Journal of Developmental Origins of Health and Disease, 9*(1), 20–29.

Mahindra, M. C. (2020). *Food security and farm mechanisation.* AGRIFOOD Magazine.

Mahiyagi. (2020). Choosing a philosophy of research: Differences between positivist and naturalist-constructionist approaches. In *Research philosophy and qualitative interviews paradigms: An illustration of the differences in practice variations on the core paradigm.*

Makini, F. W., Makelo, M. N., & Kamau, G. M. (2018). Agricultural extension system in Kenya: Evolution, challenges, and opportunities. *Journal of Agricultural Science and Technology, 19*(1), 23–42.

Makini, F.W., Mulinge, W., Mose, L., Salasya, B., Kamau, G., Makelo, M., and On'gala, J. (2018). Impact of agricultural innovation platforms on smallholder livelihoods in Eastern and Western Kenya. *FARA Research Reports, 2*(6): PP 18

Manda, J., Alene, A. D., Gardebroek, C., Kassie, M., & Tembo, G. (2016). Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. *Journal of Agricultural Economics, 67*(1), 130–153. https://doi.org/10.1111/1477-9552.12127

Mango, N. M. (2018). The role of crop diversification in improving household food security in Central Malawi.

Mango, N., Zamasiya, B., Makate, C., Nyikahadzoi, K., & Siziba, S. (2018). Factors influencing household food security among smallholder farmers in the Mudzi district of Zimbabwe. *Development Southern Africa, 31*(4), 625–640. https://doi.org/10.1080/0376835X.2014.911694

Mark, W. R., Jawoo, K., & Stanley, R. (2014). *Food security in a world of natural resource scarcity: The role of agricultural technologies.* International Food Policy Research Institute.

Matheka, G., & Achieng, A. (2021, June). *Twiga upgrades 'Soko Yetu' platform to enhance service delivery*. *HapaKenya.* Retrieved from https://hapakenya.com/2021/06/15/twiga-upgrades-soko-yetu-platform-to-enhance-service-delivery/

Mbow, C., Rosenzweig, C., Barioni, L. G., Benton, T. G., Herrero, M., Krishnapillai, M., & Waha, K. (2019). Agroforestry and food security in Africa: Challenges and opportunities. *Global Change Biology, 25*(3), 1178–1190.

McCombes, S. (2022, October 10). *Descriptive research: Definition, types, methods & examples.* Scribbr. Retrieved from https://www.scribbr.com/methodology/descriptive-research/

Meiguran, M., & Basweti, E. (2016). Influence of farmer level of education on the practice of improved agricultural technologies: A case of Nyamusi Division, Kenya. *International Journal of Recent Research in Interdisciplinary Sciences (IJRRIS), 3*(3), 19-27.

Mekonnen, H. D., Tesfaye, D., & Alemayehu, G. (2021). The impact of improved agricultural technologies on household food security of smallholders in Central Ethiopia: An endogenous switching estimation. *World Food Policy.*

Mohajan, H. K. (2017, December). Two criteria for good measurements in research: Validity and reliability. *Annals of Spiru Haret University Economic Series.* Retrieved from https://www.researchgate.net/publication/322036403

Mohammad, E., & Majid, A. (2018). Agricultural mechanization: A key to food security in developing countries—Strategy formulation for Iran. *Agriculture and Food Security, 2*(4): 245-256

Mohammed, K., Batung, E., Saaka, S. A., Kansanga, M. M., & Luginaah, I. (2023). Determinants of mechanized technology adoption in smallholder agriculture: Implications for agricultural policy. *Land Use Policy, 129*, 106666. https://doi.org/10.1016/j.landusepol.2023.106666

Molosiwa, L. E. (2019). Agricultural mechanization, a key input to food security that Botswana should consider. *Acta Scientific Agriculture, 3*(8), 16–20. https://doi.org/10.31080/ASAG.2019.03.0575

Mrema, G. C., Baker, D., & Kahan, D. (2018). *Agricultural mechanization in Sub-Saharan Africa: Time for a new look.* Food and Agriculture Organization.

Mugenda, O., & Mugenda, A. (2019). *Quantitative and qualitative approaches: Assessing the extension staff farm visits frequency effects on greenhouse technology performance in small-scale farms in Gusii Highlands, Kenya.* Nairobi, Kenya.

Murendo, C., Nhau, B., Mazvimavi, K., Khanye, T., & Chivenge, P. (2018). Social capital and adoption of climate-smart agriculture technologies among smallholder farmers: Evidence from Zimbabwe. *International Journal of Climate Change Strategies and Management, 10*(2), 217–235.

Murendo, C., Wollni, M., & Mugabi, N. (2018). Social networks and adoption of mobile phones in agricultural extension: Evidence from rural Zimbabwe. *World Development, 105*, 230–243.

Musomba, R., Nyang'au, J., & Ochieng, P. (2020). The role of mechanization in transforming small-scale farming in Kenya. *Journal of Agricultural Economics and Rural Development, 7*(2), 45–58.

Mustafa, K., & Randal, M. (1999). *For hunger-proof cities: Sustainable urban systems.* International Development Research Centre.

Musyoka, P. K., Onjala, J., & Mureithi, L. P. (2020). Infrastructure growth, household vulnerability, and response to shocks in Kenya. *African Journal of Economic Review, 8*(1), 235–250.

Mutea, E., & Ritho, S. (2020). Applying the theory of access to food security among smallholder family farmers around Northwest Mt. Kenya. *Sustainability.*

Mutea, E., Bottazzi, P., Jacobi, J., Kiteme, B., Speranza, C. I., & Rist, S. (2019). Livelihoods and food security among rural households in the north-western Mount Kenya region. *Frontiers in Sustainable Food Systems, 3.*

Mutea, E., Hossain, M. S., Ahmed, A., & Speranza, C. I. (2022). Shocks, socio-economic status, and food security across Kenya: Policy implications for achieving the Zero Hunger goal. *Environmental Research Letters, 17*(9), 094028.

Mwangi, M., & Kariuki, S. (2015). Factors Determining the Adoption of New Agricultural Technology by Small Scale Farmers in Developing Countries. *Journal of Economics and Sustainable Development, 6*, 208-216.

Nabuurs, G.-J. R. (2022). *Agriculture, forestry and other land uses (AFOLU) in IPCC, Climate Change 2022: Mitigation of Climate Change; Working Group III Contribution to the Sixth Assessment Report.* Cambridge University Press. https://doi.org/10.1017/9781009157926.009

Ndoro, J. T., Mudhara, M., & Chimonyo, M. (2020). Livestock ownership, food security and child nutritional outcomes in rural Zimbabwe. *Food Policy, 94*, 101–113. https://doi.org/10.1016/j.foodpol.2020.101913

Negrete, J. C. (2019). *The role of agricultural mechanization in food security. Food security, 5*(6):46-60

Ng'endo, M., Bhagwat, S., & Keding, G. B. (2016). Influence of seasonal on-farm diversity on dietary diversity: A case study of smallholder farming households in Western Kenya. *Ecology of Food and Nutrition, 55*(4), 403–427. https://doi.org/10.1080/03670244.2016.1200037

Nguyen, H. (2018). *Sustainable food systems.* Food and Agriculture Organization.

Ngwilizi, D., Selejio, O., & Ruhinduka, R. D. (2024). The Effect of Intra-household Mobile Phone Use on Household Food and Nutrition Security in Tanzania. *The African Review* (published online ahead of print 2024). https://doi.org/10.1163/1821889x-bja10128

Nicholas, E., & Anderson, J. (2018). Review of sustainability in the food system. *Agricultural Systems Journal, 1(2): 134-156*

Nyabuto, W. (2022). Factors affecting food security in rural households in Kenya; A case of Muchonoke Sub-Location, Embu County. *The Strategic Journal of Business & Change Management, 9* (3), 349 -367.

O'Ajao, K., Ojofeitimi, E., Adebayo, A., Fatusi, A., & Afolabi, O. (2010). Influence of family size, household food security status, and child care practices on the nutritional status of under-five children in Ile-Ife, Nigeria. *African Journal of Reproductive Health, 14*(4), 117–126.

OECD/FAO. (2022). *OECD-FAO Agricultural Outlook 2022-2031*. Paris: OECD Publishing. Retrieved from https://doi.org/10.1787/f1b0b29c-en

Ogenga, J. O., Mugalavai, E. M., & Nyandiko, N. O. (2018, August). *Impact of rainfall variability on food production under rainfed agriculture in Homa Bay County, Kenya*..

Ogunlela, Y. I., & Mukhtar, A. A. (2009). Gender issues in agriculture and rural development in Nigeria: The role of women. *Human Development, 15*(5), 10–25.

Ogutu, S. O., Gödecke, T., & Qaim, M. (2020). Agricultural commercialization and nutrition in smallholder farm households. *Journal of Agricultural Economics, 71*(2), 534–555. https://doi.org/10.1111/1477-9552.12359

Olasehinde-Williams, G., & Fakunle, F. F. (2020). Pathway to achieving sustainable food security in Sub-Saharan Africa: The role of agricultural mechanization. *Journal of Labour and Society.*

Ouma, M. A., Onyango, C. A., Ombati, J. M., & Mango, N. (2020). Innovation platform for improving rice marketing decisions among smallholder farmers in Homa Bay County, Kenya. *Cogent Food & Agriculture*.

Owuor, G., Oluoch-Kosura, W., & Wambugu, S. (2020). Livelihood diversification and food security among smallholder households in Kenya. *Development in Practice, 30*(2), 168–179.

Pingali, P. (2007). Agricultural mechanization: Adoption patterns and economic impact. *Handbook of Agricultural Economics, 3*, 2779–2805.

Pretty, J., & Jules, P. (2018, November 23). *Intensification for redesigned and sustainable agricultural systems*. *Science, 362*.

Pretty, J., Benton, T. G., Bharucha, Z. P., Dicks, L. V., & Flora, C. B. (2018). Global assessment of agricultural sustainability and food security. *Nature Sustainability, 1*(8), 441–447.

Rajput, V. D., & Saraf, A. (2022). *Emerging tools for sustainable agriculture and food security*. Deepika Book Agency.

Reincke, K., Vilvert, E., Fasse, A., Graef, F., Sieber, S., & Lana, M. A. (2018). Key factors influencing food security of smallholder farmers in Tanzania and the role of cassava as a strategic crop. *Food Security, 1*, 1–14.

Research Connections. (2023, February 16). *Descriptive research studies*. Researcher.

Robertson, M. W. (2014). *Food security in a world of natural scarcity: The role of agricultural technologies*. Washington, DC: International Food Policy Research Institute.

Rubhara, T. (2020, July). *Determinants of use of farm mechanization services in emerging farmers, North West Province, South Africa*. *Journal of Agribusiness and Rural Development*.

Safaricom. (2017). *Digifarm*. Retrieved from https://www.safaricom.co.ke/media-center-landing/frequently-asked-questions/digifarm

Sagar, B. M. (2018). *Agriculture data analytics in crop yield estimation: A critical review*. *Indonesian Journal of Electrical Engineering and Computer Science*.

Saunders, M. L. (2007). *Research methods for business students* (4th ed.). Financial Times Prentice Hall, Edinburgh Gate, Harlow.

Sheahan, M., & Barrett, C. B. (2017). Food loss and waste in Sub-Saharan Africa. *Food Policy, 70*, 1–12.

Shukla, S. (2020, June). *Concept of population and sample*. *ResearchGate*.

Sibhatu, K. T., & Qaim, M. (2017). Rural food security, subsistence agriculture, and seasonality. *PLOS ONE, 12*(10), e0186406. https://doi.org/10.1371/journal.pone.0186406

Sibhatu, K. T., Krishna, V. V., & Qaim, M. (2015). Production diversity and dietary diversity in smallholder farm households. *Proceedings of the National Academy of Sciences, 112*(34), 10657–10662. https://doi.org/10.1073/pnas.1510982112

Sileyew, K. J. (2019, August). *Research design and methodology*. Retrieved from https://www.researchgate.net/publication/335110374

Smith, J., & Todd, P. (2005). Does matching overcome LaLonde's critique of non-experimental estimators? *Journal of Econometrics, 125*(1–2), 305–353.

Smith, P., & Olesen, J. (2010). *Synergies between the mitigation of, and adaptation to, climate change in agriculture*. *Journal of Agricultural Science*.

Squires, V. R. (2020). *Agricultural productivity and food security*.

Suzann, G., & Associates. (2004). *Local capacity building in Title II food security projects: A framework*. *Democracy, Conflict, and Humanitarian Assistance Office of Food for Peace Operations: Occasional Paper #3*. Washington, DC: FHI 360/FANTA.

Takeshima, H. (2017). Custom-hired tractor services and returns to scale in smallholder agriculture: A production function approach. *Agricultural Economics, 48*(1), 1–14.

Takeshima, H., & Liu, Y. (2019). *Determinants of agricultural machinery adoption intensities in Ghana*. *International Food Policy Research Institute*. Washington, DC: International Food Policy Research Institute.

The World Bank. (2019). *Kenya economic update: Transforming agricultural productivity to achieve food security for all*. Nairobi: The World Bank Group.

Timmer, C. P. (2017). *Food security, structural transformation, markets and government policy*. *Asia and the Pacific Policy Studies*.

Tong, K., & World Food Programme (WFP). (2020, May 5). *Hello Tractor: Innovating in the agri-sharing economy*. *WFP Innovation Accelerator*. Retrieved from https://wfpinnovation.medium.com/hello-tractor-innovating-in-the-agri-sharing-economy-85b9de3e8688

Uddin, M. N., & Hamiduzzaman, M. (2011, July). *The philosophy of science in social research*. *ResearchGate*. Retrieved from https://www.researchgate.net/publication/228286943

United Nations Development Programme (UNDP). (2010). *Capacity development: Measuring capacity*. New York: UNDP.

United Nations. (2018). *The 2030 Agenda and the Sustainable Development Goals: An opportunity for Latin America and the Caribbean* (LC/G.2681-P/Rev.3). Santiago, Chile: United Nations.

van Ittersum, M. K., van Bussel, L. G. J., Wolf, J., & Grassini, P. (2016). Can sub-Saharan Africa feed itself? *Proceedings of the National Academy of Sciences, 113*(52), 14964–14969.

Van Loon, J., Woltering, L., Krupnik, T. J., Baudron, F., Boa, M., & Govaerts, B. (2020). Scaling agricultural mechanization services in smallholder farming systems: The role of private sector involvement. *Sustainability, 12*(5), 1982.

von Grebmer, K., Bernstein, J., Alders, R., Dar, O., Kock, R., Rampa, F., Wiemers, M., Acheampong, K., Hanano, A., Higgins, B., Ní Chéilleachair, R., Foley, C., Gitter, S., & Ekstrom, K. (2020). *2020 Global Hunger Index: One decade to zero hunger—Linking health and sustainable food systems*. Welthungerhilfe; Concern Worldwide. https://www.globalhungerindex.org/pdf/en/2020.pdf

Waswa, L. M., Jordan, I., Herrmann, J., Krawinkel, M. B., & Keding, G. B. (2012). Household food security and dietary diversity in different agro-ecological zones in Western Kenya.

Wengawenga, D. M. (2020). *Technology can enhance food security in agriculture in Africa*. Retrieved from https://agritech-africa.com/2019/10/16/technology-enhancing-food-security-in-agriculture/#:~:text=Regionally%20and%20globally%2C%20the%20pursuit%20of%20food%20security,surplus%20to%20trade%20with%20counterparts%20in%20food-deficit%20areas

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming: A review. *Agricultural Systems, 153*, 69–80.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data.* Prentice-Hall International Inc.

Wordofa, M., Hassen, J., & Endris, G. (2021, October 5). *Adoption of improved agricultural technology and its impact on household income: A propensity score matching estimation in eastern Ethiopia. Agriculture and Food Security*. Retrieved from https://doi.org/10.1186/s40066-020-00278-2

World Bank. (2021). *South Sudan economic update: Support to agricultural investment and economic reforms critical for sustainable food security*. Juba.

World Vision International. (2021, March). *The basics of food security. World Vision Canada*. Retrieved from https://www.worldvision.ca/stories/food/the-basics-of-food-security

Zamora, E. (2016). *Value chain analysis: A brief review. Asian Journal of Innovation and Policy*.

Zewdie, T. (2018). Review on factors affecting adoption of improved maize seed technology in Ethiopia. *International Journal of Agriculture Extension and Social Development*, *3*(11): 3456-490

APPENDIX Ia: LETTER TO THE RESPONDENTS

Malaki Nyakado Owino
Strathmore Business School
P.O. Box 59857 – 00200,
Nairobi.

Dear Respondent,

RE: INTRODUCTION LETTER FOR DATA COLLECTION

Greetings, I am Malaki Nyakado Owino, a student at the Strathmore Business School pursuing Master's in management in Agribusiness. I am currently undertaking the thesis research on "Factors influencing Food security among the cereal farmers in Homa Bay County, Kenya." The main goal of the study is to help relevant stakeholders and cereal farmers design their agricultural production systems to address the main Food insecurity problems among the smallholder farmers. The study also aims to enlighten smallholder farmers on how they can improve their agricultural productions sustainably and increase their incomes.

To this extent, I kindly request you to accept and answer these research questions as truthful as possible to enhance the research validity and reliability. Be assured that all the information shared with the researcher shall remain confidential and will only be used for the purposes of this research and if any, in research that will be aimed at further understanding of the results and recommendations of this initial research. You are also at liberty to decline this request. Thank you.

Best Regards,

Malaki Nyakado Owino
+254725144989

APPENDIX Ib: NACOSTI PERMIT

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **953158**

Date of Issue: **30/July/2025**

RESEARCH LICENSE

This is to Certify that Mr.. Malachi Nyakado Owino of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Homabay on the topic: DETERMINANTS OF FOOD SECURITY AMONG SMALL-SCALE CEREAL FARMERS IN HOMA BAY COUNTY, KENYA for the period ending : 30/July/2026.

License No: **NACOSTI/P/25/4177610**

953158

Applicant Identification Number

Ag. Director General

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

See overleaf for conditions

THE SCIENCE, TECHNOLOGY AND INNOVATION ACT, 2013 (Rev. 2014)
Legal Notice No. 108: The Science, Technology and Innovation (Research Licensing) Regulations, 2014

The National Commission for Science, Technology and Innovation, hereafter referred to as the Commission, was the established under the Science, Technology and Innovation Act 2013 (Revised 2014) herein after referred to as the Act. The objective of the Commission shall be to regulate and assure quality in the science, technology and innovation sector and advise the Government in matters related thereto.

CONDITIONS OF THE RESEARCH LICENSE

1. The License is granted subject to provisions of the Constitution of Kenya, the Science, Technology and Innovation Act, and other relevant laws, policies and regulations. Accordingly, the licensee shall adhere to such procedures, standards, code of ethics and guidelines as may be prescribed by regulations made under the Act, or prescribed by provisions of International treaties of which Kenya is a signatory to.
2. The research and its related activities as well as outcomes shall be beneficial to the country and shall not in any way;
   i. Endanger national security
   ii. Adversely affect the lives of Kenyans
   iii. Be in contravention of Kenya's international obligations including Biological Weapons Convention (BWC), Comprehensive Nuclear-Test-Ban Treaty Organization (CTBTO), Chemical, Biological, Radiological and Nuclear (CBRN).
   iv. Result in exploitation of intellectual property rights of communities in Kenya
   v. Adversely affect the environment
   vi. Adversely affect the rights of communities
   vii. Endanger public safety and national cohesion
   viii. Plagiarize someone else's work
3. The License is valid for the proposed research, location and specified period.
4. Neither the license nor any rights thereunder are transferable.
5. The Commission reserves the right to cancel the research at any time during the research period if in the opinion of the Commission the research is not implemented in conformity with the provisions of the Act or any other written law.
6. The Licensee shall inform the relevant County Director of Education, County Commissioner and County Governor before commencement of the research.
7. Excavation, filming, movement, and collection of specimens are subject to further necessary clearance from relevant Government Agencies.
8. The License does not give authority to transfer research materials.
9. The Commission may monitor and evaluate the licensed research project for the purpose of assessing and evaluating compliance with the conditions of the License.
10. The Licensee shall submit one hard copy, and upload a soft copy of their final report (thesis) onto a platform designated by the Commission within one year of completion of the research.
11. The Commission reserves the right to modify the conditions of the License including cancellation without prior notice.
12. Research, findings and information regarding research systems shall be stored or disseminated, utilized or applied in such a manner as may be prescribed by the Commission from time to time.
13. The Licensee shall disclose to the Commission, the relevant Institutional Scientific and Ethical Review Committee, and the relevant national agencies any inventions and discoveries that are of National strategic importance.
14. The Commission shall have powers to acquire from any person the right in, or to, any scientific innovation, invention or patent of strategic importance to the country.
15. Relevant Institutional Scientific and Ethical Review Committee shall monitor and evaluate the research periodically, and make a report of its findings to the Commission for necessary action.

National Commission for Science, Technology and
Innovation(NACOSTI),
Off Waiyaki Way, Upper Kabete,
P. O. Box 30623 - 00100 Nairobi, KENYA
Telephone: 020 4007000, 0713788787, 0735404245
E-mail: dg@nacosti.go.ke
Website: www.nacosti.go.ke

APPENDIX Ic: SU ETHICAL REVIEW LETTER

Strathmore UNIVERSITY

22nd April 2025

Mr Owino Malachi,
Malaki.owino@strathmore.edu

Dear Mr Owino,

<u>RE: Determinants of Food Security Among Small-Scale Cereal Farmers in Homa Bay County, Kenya</u>

This is to inform you that SU-ISERC has reviewed and **approved** your above SU- **Masters** proposal. Your application reference number is **SU-ISERC2907/25.** The approval period is from **22nd April 2025 to 21st April 2026.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

APPENDIX II: PARTICIPANTS CONSENT FORM

SECTION I:

Researcher: Malaki Nyakado Owino
Institution: Strathmore Business School (SBS)
Research Title: Determinants of Food Security among Small-scale Cereal Farmers in Homa Bay County, Kenya
Participant Information:
Initials: ....
Gender: ....
Place of Residence: ....
Contact Details: ....
Interview Venue: ....

SECTION II: Study Information Sheet

2.1 Purpose of the Study

This research is part of the requirements for the Master's degree in Agribusiness Management at Strathmore Business School. The study seeks to understand the various factors that affect food security among smallholder cereal farmers in Homa Bay County.

2.2 Voluntary Participation

Participation in this study is entirely voluntary. Even after giving consent, you are free to withdraw from the study at any stage without any consequences.

2.3 Who Can Participate?

Adults aged 18 years and above who are actively involved in small-scale cereal farming—specifically maize, sorghum, or rice—in Homa Bay County are eligible to participate.

2.4 Who Cannot Participate?

Individuals below 18 years of age and those not engaged in cereal farming are not eligible for this study.

2.5 What Does Participation Involve?

As a participant and beneficiary of agricultural policies, your insights will be valuable in informing future government decisions and creating a more supportive environment for smallholder farmers.

2.6 Are There Any Risks Involved?

No. This study presents no known risks or harm to participants.

2.7 What Are the Benefits of Participating?

Your contribution will help shape better farming practices and guide policies that aim to improve food security and farmer well-being in your community and beyond.

2.8 What Happens If I Choose Not to Participate?

There will be no consequences if you choose not to participate. Participation is entirely your choice.

2.9 Who Will Access My Information?

All data collected will be treated as confidential and used solely for research purposes. However, the results may be shared to support policy recommendations and future studies.

2.10 Who to Contact for More Information?

If you have any questions or need further clarification, feel free to contact:

Researcher: Malaki Nyakado Owino – +254 725 144 989

Supervisor: Dr. Everlyne Makhanu – via Strathmore Business School

Independent Contact:

The Secretary, Strathmore University Institutional Ethics Review Board

P.O. BOX 59857, 00200 Nairobi

Email: ethicsreview@strathmore.edu | Tel: +254 703 034 375

Consent Declaration

I, ____________________________, confirm that the purpose of this study has been clearly explained to me. I understand what is required, and I have had the opportunity to ask questions and receive satisfactory answers. I also understand that I can withdraw at any time without giving a reason.

Please tick the appropriate boxes:

☐ I AGREE to take part in this research study

☐ I DO NOT AGREE to take part in this research study

Regarding storage of my completed questionnaire:

☐ I AGREE for my data to be stored for future analysis

☐ I DO NOT AGREE for my data to be stored for future analysis

Participant Name: ....

Signature: ....

Date: ....

For Official Use (Researcher Only):

I, ____________________________, confirm that I have followed the approved procedures, provided all necessary information to the participant, and ensured they have understood the nature and purpose of this study.

Researcher's Signature: ____________________

Date: ____________________

Name: ____________________

APPENDIX III: QUESTIONNAIRE FOR CEREAL FARMERS

PART 1: FARM DEMOGRAPHIC INFORMATION

No	Question	Responses
1.1	Gender of the farmer?	1.Male 2. Female
1.2	Marital status of the farmer?	1. Married 2. Single 3. Divorced/Separated 4. Widow 5. Widower
1.3	Age of the farmer?	1. 18-35 2. 36-49 3. Above 49
1.4	Level of education of the farmer?	1. Primary 2. Secondary 3. Tertiary
1.5	Main occupation of the household head?	1. Formally employed, 2. self-employed 3. Farming
1.6	What is you household size	
1.6	How long have you practised cereal farming	1. Less than 3 years 2. 3- 6 years. 3. Above 6 years
1.7	Which variety of maize do you grow?	1. Improved 2. Local 3. Both
1.8	Which variety of sorghum do you grow?	1. Improved 2. Local 3. Both
1.9	Which variety of rice do you grow?	1. Improved 2. Local 3. Both
1.10	Do you receive (county/national) government subsidy for inputs	1. Yes 2. No
1.11	Total land size owned in acres	
1.11	Land tenure system	1. Owned 2. Leased 3. Gifted/family/communal
1.12	Access to credit	1. Yes, 2. No
1.13	Access to markets	1. Yes, 2.No
1.14	Are you a member of production and maketing group or association	2.
1.15	How many livestock do you own?	1. Dairy 2. BULLS 3. SHOATs 4. Poultry
1.16	Do you have access to extension services	1.Yes, 2.No

PART 2: AGRICULTURAL MECHANIZATION

2.1	In which farming activities do you apply farm mechanization in your land? (Please tick where possible)	1.Ploughing 2. Harrowing 3. Planting 4. Weeding 5. Irrigation 6. Harvesting
2.2	Do you own or hire the machinery/tools used above?	1. Self-owned 2. Hired 3. Free
2.3	Which machinery did you use in maize production in the last season?	1. Animal traction 2. Tractor 3. Irrigation equipment 4. Harvesting equipment 5. N/A
2.4	Which machinery do you use in sorghum production in the last season?	1. Animal traction 2. Tractor 3. Irrigation equipment 4. Harvesting equipment 5. N/A
2.5	Which machinery do you use in rice production in the last season?	1. Animal traction 2. Tractor 3. Irrigation equipment 4. Harvesting equipment 5. N/A
2.6	Does the government subsidize the cost of mechanization	1. Yes 2. No

PART 3: AGRICULTURAL TECHNOLOGIES

3.1. How much are you aware of the following market information technologies? (Please tick only one)

Technology	1=Not Aware	2=Moderately Aware	3= Very Aware
Mbegu Choice			
Hello tractor			
DigiFarm			
Soko Yetu			
My Fugo			
Mkulima Young			
Farm Kenya			
Radio			
Social media			

3.2. Famers knowledge level of existing technologies (Please tick only one)

Technology	1=Basic knowledge	2=Moderately knowledgeable	3= Very knowledgeable
Mbegu Choice			
Hello tractor			
DigiFarm			
Soko Yetu			
My Fugo			
Mkulima Young			
Farm Kenya			
Radio			
Social media			

3.3. How did you first learn about the technology? (Please tick only one)

Technology	Private/NGO extension officers	Government extension officers	Cooperative/fellow farmers
Mbegu Choice			
Hello tractor			
DigiFarm			
Soko Yetu			
My Fugo			
Mkulima Young			
Farm Kenya			
Radio			

Social media			

3.4. What level of training have you received in any of the technologies? (Please tick only one)

Technology	Basic training	Modest training	Extensive training
Mbegu Choice			
Hello tractor			
DigiFarm			
Soko Yetu			
My Fugo			
Mkulima Young			
Farm Kenya			
Radio			
Social media			

3.5. How frequently do you use the technologies in your agribusiness in sourcing for inputs, obtaining market information or marketing your products i.e., maize, sorghum, or rice.
(Please tick only one)

Technology	Daily	Weekly	Monthly	Yearly	Have not used completely
Mbegu Choice					
Hello tractor					
DigiFarm					
Soko Yetu					
My Fugo					
Mkulima Young					
Farm Kenya					
Radio					
Social media					

3.6. How would you rate the ease of use of the technologies? (Please tick only one)

Technology	1=Easy to use	2=Moderately easy to use	3=Difficult to use
Mbegu Choice			
Hello tractor			
DigiFarm			
Soko Yetu			
My Fugo			

Mkulima Young			
Farm Kenya			
Radio			
Social media			

3.7 In your opinion, would you agree/Disagree that these technologies are useful in Agribusiness? (Please tick only one)

Technology 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree	**Sourcing for inputs**		**Obtaining market information**		**Marketing of produce**	
Mbegu Choice						
Hello tractor						
DigiFarm						
Soko Yetu						
My Fugo						
Mkulima Young						
Farm Kenya						
Radio						
Social media						

PART 4: SUSTAINABLE AGRICULTURAL PRACTICES

<table>
<tr><td>4.1</td><td colspan="5">Please indicate if you have used following farming practices in your farm in the past?</td><td></td></tr>
<tr><td></td><td></td><td colspan="2">1.Yes</td><td colspan="2">1. No</td><td>How many seasons have you used the practices</td></tr>
<tr><td></td><td>Conservation agriculture
1.Minimal tillage
2. Crop rotation
3. Mulching
4. Intercropping
5. Cover cropping</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td></td><td>Agroforestry</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td></td><td>Crop diversification</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td></td><td>Integrated Pest Management (push pull)</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td></td><td>Organic farming-compost and natural fertilizers</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td></td><td>Water conservation techniques (drip irrigation)</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td></td><td>Renewable energy sources (solar-powered irrigation)</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td>4.3</td><td>How did you learn about the application of sustainable agricultural practices</td><td>Self</td><td colspan="2">Government extension officer</td><td>Private/NGO extension office</td><td></td></tr>
<tr><td>4.4</td><td>What marketing channels did you use in your agribusiness?</td><td>1. Direct to consumers</td><td colspan="2">2. Middlemen/Brokers</td><td>3. Cooperatives/Agro processors</td><td></td></tr>
</table>

PART 5: FOOD SECURITY INDICES DECISIONS, EXPENDITURE, CONSUMPTION AND FOOD SECURITY

N1	Who in your family usually has the final say on decisions related to your health? [SR]	0.Yourself 1.Your Spouse 2.Another Male HH member 3.Another Female HH member 4. Jointly 99. Others specify
N2	Who in your family usually has the final say on decisions related to large household assets purchases? [SR]	0.Yourself 1.Your Spouse 2.Another Male HH member 3.Another Female HH member 4. Jointly 99. Others specify
N3	Who in your family usually has the final say on decisions related to large household asset sale? [SR]	0.Yourself 1.Your Spouse 2.Another Male HH member 3.Another Female HH member 4. Jointly 99. Others specify
N4	How would you rate your household health?[SR]	1. Excellent 2. Good 3. Fair 4. Poor 5. Very poor
N5	What was your household's income from the following sources during the past 12 months in KES? (Include the income of all household members) [OA] (Ask for their best guess if they do not have records	On farm___________ Off farm _______________
N7	What is your total monthly expenditure on the following [OA] (Ask for their best guess if they do not have records	Food item_____________ Non-food item (clothing________ ________bills,___________ school_______ health,______________
N8	During the last 12 MONTHS, was there a time when:	
	You and your household were worried that you would run out of food because of a lack of money or other resources? [SR]	0.No 1. Yes, 3. Can't remember
	You and your household were unable to eat healthy and nutritious food because of a lack of money or other resources? [SR]	0.No 1. Yes, 3. Can't remember
	You and your household ate only a few kinds of foods because of a lack of money or other resources? [SR]	0.No 1. Yes, 3. Can't remember
	You and your household had to skip a meal because there was not enough money or other resources to	0.No 1. Yes, 3. Can't remember

	get food? [SR]	
	You and your household ate less than you thought you should because of a lack of money or other resources? [SR]	0.No 1. Yes, 3. Can't remember
	Your household ran out of food because of a lack of money or other resources? [SR]	0.No 1. Yes, 3. Can't remember
	You ran out of food because of a lack of money or other resources?[SR]	0.No 1. Yes, 3. Can't remember
	You and your household were hungry but did not eat because there was not enough money or other resources for food? [SR]	0.No 1. Yes, 3. Can't remember
	Your household went without eating for a whole day because of a lack of money or other resources? [SR]	0.No 1. Yes, 3. Can't remember
	You went without eating for a whole day because of a lack of money or other resources? [SR]	0.No 1. Yes, 3. Can't remember
N9	Taking into consideration ALL food sources (own food production + food purchase + help from different sources + food hunted from forest and lakes, etc.), how would you assess your family's food consumption in the past 12 months? [SR]	0.Food shortage through the year 2. Occasional food shortage 3.No food shortage but no surplus 4.Food surplus
	Household Dietary Diversity score questions	
	Now I would like to ask you the types of foods (meals and snack) you ate or drank yesterday during day and night in your household, whether at home or outside the home. Please, tell me by accurately recalling and indicate source of food	

FOOD GROUP	EXAMPLES	Code 1 =Yes 2 =No	Source of food (see codes below the table)	
			Primary source	**Secondary source**
Cereals	millet, sorghum, maize, rice, wheat			
Roots and tubers	potatoes, yams, manioc, cassava or any other foods			
Vegetables	Kales, cabbage, carrots, French beans,			
Fruits	Mangoes, oranges, pawpaws, Pineapples, water melons, passion fruits			
Meat	beef, pork, lamb, goat, rabbit wild game, chicken, duck, or other birds, liver, kidney, heart, or other organ			
Eggs	eggs			
Fish and sea foods	fresh or dried fish or shellfish			
Pulses/ legumes/ nuts	beans, peas, lentils, groundnuts			

Milk and milk products	cheese, yogurt, milk or other milk products			
Oils/fats	Oil/ fat			
Sugar/honey	Sugar, honey			
Miscellaneous	Coffee, tea, spices, condiments			

Household Food Consumption Score (HFCS) Questions

In the past 7 days, how many days did your household consume the following food groups?
(Record the number of days out of 7)

Food Group	Examples	Did you consume this food in the last 7 days 1-Yes, 0=No	Number of Days Consumed (0–7)
1. Cereals	Maize, rice, sorghum, wheat, millet, bread		___
2. Pulses/Legumes	Beans, lentils, green grams, cowpeas, pigeon peas		___
3. Vegetables	Green leafy vegetables, carrots, tomatoes		___
4. Fruits	Mangoes, bananas, oranges, pawpaw		___
5. Meat/Fish/Eggs	Beef, chicken, goat, fish, eggs		___
6. Dairy Products	Milk, yogurt, cheese		___
7. Oils/Fats	Cooking oil, butter, ghee		___
8. Sugar/Honey	Sugar, honey, sweetened foods		___

Household Food Insecurity Experience Scale (HFIAS) Questions

In the past 30 days, did you or any household member experience the following due to a lack of food or lack of money to buy food?

Question	Response Options
1. Were you worried that your household would not have enough food?	☐ Yes ☐ No
2. Were you or any household member unable to eat the kinds of foods you preferred due to lack of resources?	☐ Yes ☐ No
3. Did you or any household member eat a limited variety of foods due to lack of resources?	☐ Yes ☐ No
4. Did you or any household member eat food that you did not want to eat because of lack of money or resources?	☐ Yes ☐ No
5. Did you or any household member eat less than they felt they should because of lack of money or resources?	☐ Yes ☐ No

6. Did you or any household member skip a meal because there was not enough money or food?	☐ Yes ☐ No
7. Did you or any household member go a whole day without eating because of lack of money or food?	☐ Yes ☐ No
8. Did you or any household member feel weak or dizzy because they did not have enough food?	☐ Yes ☐ No
9. Did any household member go to sleep hungry because there was not enough food?	☐ Yes ☐ No

In the past 12 months, due to lack of money or other resources, have you or any member of your household:

Question	**Response Options**
1. Worried about not having enough food to eat?	☐ Yes ☐ No
2. Been unable to eat healthy and nutritious food?	☐ Yes ☐ No
3. Eaten only a few kinds of food because of lack of money or resources?	☐ Yes ☐ No
4. Had to skip a meal because there was not enough money or food?	☐ Yes ☐ No
5. Eaten less than you thought you should because of lack of money or resources?	☐ Yes ☐ No
6. Run out of food and had no money to get more?	☐ Yes ☐ No
7. Been hungry but did not eat because there was not enough money or food?	☐ Yes ☐ No
8. Gone a whole day without eating because there was not enough money or food?	☐ Yes ☐ No

------------------THE END----------------------

APPENDIX IV: KEY INFORMANT INTERVIEW (KII) GUIDE

Introduction and Consent:

Thank you for taking the time to participate in this interview. The purpose of this discussion is to gain insights into the influence of agricultural mechanization, innovative agricultural technologies, and sustainable agricultural practices on food security in Homa Bay County. Your responses will remain confidential and will only be used for research purposes.

1. Agricultural Mechanization and Food Security

i. What types of agricultural mechanization are commonly used by cereal farmers in Homa Bay County?
ii. How accessible are mechanized farming tools and equipment to smallholder farmers?
iii. In what ways has mechanization influenced productivity and food security in the region?

2. Innovative Agricultural Information Technologies

i. What digital or technological platforms do farmers use to access agricultural information?
ii. How effective are mobile apps, SMS services, and extension services in disseminating farming knowledge?
iii. What challenges do farmers face in adopting these agricultural technologies?

3. Sustainable Agricultural Practices

i. How have these practices influenced soil fertility, crop yields, and long-term food security?
ii. What are the major constraints in implementing sustainable agricultural practices?
iii. Are there any government or NGO programs supporting sustainable agriculture in the county?

4. Policy and Institutional Support

i. What role do government agencies, NGOs, or private sector stakeholders play in promoting agricultural mechanization, technology, and sustainability?
ii. What policies exist to support food security through improved farming techniques?

THE END

APPENDIX V: FOCUS GROUP DISCUSSION (FGD) GUIDE

Introduction and Consent:
Welcome and thank you for participating in this discussion. This session aims to explore your experiences and perspectives on agricultural mechanization, innovative agricultural technologies, and sustainable farming practices, and how they influence food security. Your input is valuable, and all responses will remain confidential.

1. Agricultural Mechanization and Food Security

i What types of mechanized farming tools or equipment do you use on your farms?
ii How has mechanization affected your crop yields and food availability?
iii What challenges do you face in accessing or using agricultural machinery?
iv What support would help improve mechanization for smallholder farmers?

2. Innovative Agricultural Information Technologies

i. What digital tools or platforms do you use to access farming information?
ii. How useful are these technologies in improving farming decisions and food security?
iii. What barriers prevent you from adopting these technologies?
iv. How can access to agricultural information be improved for farmers?

3. Sustainable Agricultural Practices

i. What farming practices do you use to maintain soil fertility and increase productivity?
ii. How have these practices impacted your farm yields and household food security?
iii. What challenges do you face in implementing sustainable farming practices?
iv. What support or training would help you adopt more sustainable farming methods?

APPENDIX VI: STATA OUTPUTS

OUTPUT 1: OBJECTIVE 1

```
. regress mechanization gender2 maritalstatus2 age education household_size farming_experience
live
> tsock_ownership main_occupation2 totalincome access_credit access_extensionservice

      Source |       SS           df       MS      Number of obs   =       473
-------------+----------------------------------   F(11, 461)      =      5.84
       Model |  10.5251339        11  .956830355   Prob > F        =    0.0000
    Residual |  75.4790944       461  .163729055   R-squared       =    0.1224
-------------+----------------------------------   Adj R-squared   =    0.1014
       Total |  86.0042283       472  .182212348   Root MSE        =    .40463

------------------------------------------------------------------------------------------
            mechanization |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
                 gender2 |  -.0349607   .0406309    -0.86   0.390    -.1148056    .0448841
          maritalstatus2 |   .1631235   .0533624     3.06   0.002     .0582597    .2679873
                     age |  -.0407191   .0333375    -1.22   0.223    -.1062315    .0247932
               education |  -.0021087   .0234997    -0.09   0.929    -.0482885    .0440711
          household_size |  -.0149124   .0072052    -2.07   0.039    -.0290716   -.0007533
      farming_experience |   .0060627   .0021278     2.85   0.005     .0018813    .0102441
     livetsock_ownership |   .1261252   .0429429     2.94   0.003     .0417372    .2105133
        main_occupation2 |   .0837023   .0515921     1.62   0.105    -.0176826    .1850872
             totalincome |   3.11e-07   1.49e-07     2.09   0.037     1.85e-08    6.04e-07
           access_credit |  -.0090244   .0406902    -0.22   0.825    -.0889856    .0709369
access_extensionservices |   .1932163   .0415888     4.65   0.000     .1114891    .2749435
                   _cons |   .4395067   .1324349     3.32   0.001     .1792558    .6997577
```

```
probit mechanization gender2 maritalstatus2 age education household_size farming_experience
livetsock_ownership main_occupat
> ion2 totalincome access_credit access_extensionservice

. vif

    Variable |       VIF       1/VIF
-------------+----------------------
farming_ex~e |      1.88    0.532319
         age |      1.72    0.581982
   education |      1.43    0.700988
maritalsta~2 |      1.34    0.745686
access_ext~s |      1.25    0.802761
main_occup~2 |      1.20    0.830055
     gender2 |      1.19    0.841873
household_~e |      1.18    0.850869
access_cre~t |      1.17    0.857835
livetsock_~p |      1.15    0.869908
 totalincome |      1.11    0.898779
-------------+----------------------
    Mean VIF |      1.33

. linktest

      Source |       SS           df       MS      Number of obs   =       473
-------------+----------------------------------   F(2, 470)       =     36.91
       Model |  11.6737308         2  5.83686542   Prob > F        =    0.0000
    Residual |  74.3304975       470  .158149995   R-squared       =    0.1357
-------------+----------------------------------   Adj R-squared   =    0.1321
       Total |  86.0042283       472  .182212348   Root MSE        =    .39768
```

```
------------------------------------------------------------------------------
mechanizat~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   3.305868   .8643646     3.82   0.000     1.607371    5.004366
      _hatsq |  -1.556438   .5775405    -2.69   0.007    -2.691319   -.4215565
       _cons |  -.8187603   .3183415    -2.57   0.010    -1.444309   -.1932116
------------------------------------------------------------------------------

. estat imtest

Cameron & Trivedi's decomposition of IM-test

---------------------------------------------------
              Source |       chi2     df      p
---------------------+-----------------------------
  Heteroskedasticity |     109.83     71    0.0021
            Skewness |     196.25     11    0.0000
            Kurtosis |       3.83      1    0.0503
---------------------+-----------------------------
               Total |     309.91     83    0.0000
---------------------------------------------------

. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of mechanization

         chi2(1)      =    24.07
         Prob > chi2  =   0.0000

. ovtest

Ramsey RESET test using powers of the fitted values of mechanization
       Ho:  model has no omitted variables
                 F(3, 458) =      2.72
                  Prob > F =      0.0438

.
. pscore mechanization gender2 maritalstatus2 age education household_size farming_experience
livetsock_ownership main_occupat
> ion2 totalincome access_credit access_extensionservice, pscore(p1) blockid(Blocks)comsup
level(0.001)


****************************************************
Algorithm to estimate the propensity score
****************************************************


The treatment is mechanization

   Have you |
 mechanized |
 your farm? |      Freq.     Percent        Cum.
------------+-----------------------------------
         No |        113       23.89       23.89
        Yes |        360       76.11      100.00
------------+-----------------------------------
      Total |        473      100.00


Estimation of the propensity score
```

```
Iteration 0:   log likelihood = -260.05984
Iteration 1:   log likelihood = -230.96519
Iteration 2:   log likelihood =  -230.4375
Iteration 3:   log likelihood = -230.43638

Probit regression                                 Number of obs   =        473
                                                  LR chi2(11)     =      59.25
                                                  Prob > chi2     =     0.0000
Log likelihood = -230.43638                       Pseudo R2       =     0.1139

------------------------------------------------------------------------------
mechanizat~n |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     gender2 |  -.1459255   .1471928    -0.99   0.321     -.434418    .1425671
maritalsta~2 |   .5570981   .1882712     2.96   0.003     .1880933     .926103
         age |  -.1517819   .1193842    -1.27   0.204    -.3857706    .0822069
   education |  -.0098576   .0851442    -0.12   0.908    -.1767371     .157022
household_~e |  -.0546669   .0255409    -2.14   0.032    -.1047262   -.0046076
farming_ex~e |   .0235294   .0082992     2.84   0.005     .0072633    .0397955
livetsock_~p |    .419192    .150749     2.78   0.005     .1237295    .7146546
main_occup~2 |    .249286   .1826611     1.36   0.172    -.1087233    .6072952
 totalincome |   1.25e-06   6.13e-07     2.05   0.041     5.34e-08    2.46e-06
access_cre~t |    -.04331   .1486236    -0.29   0.771    -.3346069     .247987
access_ext~s |   .6403023   .1492765     4.29   0.000     .3477258    .9328788
       _cons |  -.2459072   .4757514    -0.52   0.605    -1.178363    .6865484
------------------------------------------------------------------------------
```

```
Note: the common support option has been selected
The region of common support is [.31119972, .99722638]
```

```
Description of the estimated propensity score
in region of common support

                 Estimated propensity score
-------------------------------------------------------------
      Percentiles      Smallest
 1%     .3575158       .3111997
 5%     .4754054       .3191089
10%     .5646259       .3304901       Obs                 470
25%     .6820534       .3380384       Sum of Wgt.         470

50%     .7868877                      Mean           .7638583
                        Largest       Std. Dev.      .1453536
75%     .8804792       .9737834
90%     .9274368       .9739244       Variance       .0211277
95%     .9388766       .9817929       Skewness      -.8894411
99%      .973617       .9972264       Kurtosis       3.379153
```

```
******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************
```

```
The final number of blocks is 5

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each block
```

```
**********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************


The balancing property is satisfied


This table shows the inferior bound, the number of treated
and the number of controls for each block

  Inferior |  Have you mechanized
  of block |      your farm?
of pscore  |        No        Yes |     Total
-----------+----------------------+----------
        .2 |        10          5 |        15
        .4 |        22         28 |        50
        .6 |        53        132 |       185
        .8 |        25        195 |       220
-----------+----------------------+----------
     Total |       110        360 |       470

Note: the common support option has been selected


*******************************************
End of the algorithm to estimate the pscore
*******************************************

. psgraph, treated( mechanization ) pscore(p1) bin(50)

.
. kdensity p1 if mechanization ==0, lpattern(dash) addplot (kdensity p1 if mechanization ==1)
title ("distribution propensity
> scores") xtitle("scores") ytitle("density")

*********ATT and Biases***********
. **************Nearest Neighbour Matching******************
.
. ***************NNM(3)***********************************

. psmatch2 mechanization gender2 maritalstatus2 age education household_size farming_experience
livetsock_ownership main_occup
> ation2 totalincome access_credit access_extensionservice, outcome ( HFCSCORE )  neighbor (3)
common

Probit regression                               Number of obs     =        473
                                                LR chi2(11)       =      59.25
                                                Prob > chi2       =     0.0000
Log likelihood = -230.43638                     Pseudo R2         =     0.1139

------------------------------------------------------------------------------------------
           mechanization |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
                 gender2 |  -.1459255    .147193    -0.99   0.321    -.4344184    .1425675
          maritalstatus2 |   .5570981   .1882716     2.96   0.003     .1880926    .9261037
                     age |  -.1517819   .1193844    -1.27   0.204    -.3857709    .0822072
               education |  -.0098576   .0851443    -0.12   0.908    -.1767373    .1570222
          household_size |  -.0546669    .025541    -2.14   0.032    -.1047263   -.0046075
      farming_experience |   .0235294   .0082992     2.84   0.005     .0072632    .0397956
     livetsock_ownership |    .419192   .1507492     2.78   0.005     .1237291     .714655
        main_occupation2 |    .249286   .1826613     1.36   0.172    -.1087236    .6072956
             totalincome |   1.25e-06   6.13e-07     2.05   0.041     5.34e-08    2.46e-06
```

```
           access_credit |    -.04331   .1486239    -0.29   0.771    -.3346074    .2479874
access_extensionservices |   .6403023   .1492767     4.29   0.000     .3477254    .9328791
                   _cons |  -.2459072    .475752    -0.52   0.605    -1.178364    .6865497
------------------------------------------------------------------------------------------
----------------------------------------------------------------------------------------
        Variable     Sample |    Treated     Controls   Difference         S.E.   T-stat
----------------------------+-----------------------------------------------------------
        HFCSCORE  Unmatched | 56.3583333   45.8539823    10.504351   2.15747576     4.87
                        ATT | 56.2759104   47.1092437   9.16666667   3.05076246     3.00
----------------------------+-----------------------------------------------------------
Note: S.E. does not take into account that the propensity score is estimated.

 psmatch2: |   psmatch2: Common
 Treatment |        support
assignment | Off suppo  On suppor |     Total
-----------+----------------------+----------
 Untreated |         0        113 |       113
   Treated |         3        357 |       360
-----------+----------------------+----------
     Total |         3        470 |       473


. pstest, both

------------------------------------------------------------------------------------------
                  Unmatched |       Mean               %reduct |     t-test    |  V(T)/
Variable            Matched | Treated Control    %bias  |bias| |    t    p>|t| |  V(C)
----------------------------+----------------------------------+---------------+----------
gender2                   U | .53333   .52212      2.2         |   0.21  0.835 |     .
                          M | .53221   .64613    -22.8  -916.2 |  -3.11  0.102 |     .
                            |                                  |               |
maritalstatus2            U | .81944   .71681     24.4         |   2.37  0.018 |     .
                          M | .82073   .84127     -4.9    80.0 |  -0.73  0.465 |     .
                            |                                  |               |
age                       U | 2.2389   2.1593     10.8         |   1.01  0.314 |  0.94
                          M | 2.2381   2.2577     -2.7    75.4 |  -0.36  0.719 |  0.98
                            |                                  |               |
education                 U | 3.4083   3.4425     -3.5         |  -0.33  0.738 |  0.81*
                          M |  3.409   3.4659     -5.8   -66.8 |  -0.82  0.412 |  0.94
                            |                                  |               |
household_size            U | 5.1972   5.4513     -9.5         |  -0.84  0.401 |  1.42*
                          M | 5.2045     5.69    -18.1   -91.1 |  -2.33  0.200 |  1.20
                            |                                  |               |
farming_experience        U | 17.858   14.186     32.6         |   2.86  0.004 |  1.59*
                          M | 17.681   18.208     -4.7    85.6 |  -0.59  0.552 |  1.11
                            |                                  |               |
livetsock_ownership       U | .73056   .53982     40.3         |   3.86  0.000 |     .
                          M | .72829   .71335      3.2    92.2 |   0.44  0.657 |     .
                            |                                  |               |
main_occupation2          U |   .825   .74336     19.9         |   1.92  0.056 |     .
                          M | .82353   .85247     -7.0    64.5 |  -1.05  0.295 |     .
                            |                                  |               |
totalincome               U | 1.1e+05    74214     29.6          |    2.59  0.010 |  1.61*
                          M | 1.1e+05    90886     13.4     54.9 |    1.62  0.105 |  0.76*
                            |                                  |               |
access_credit             U | .43889   .36283     15.5         |   1.43  0.154 |     .
                          M | .43978   .44818     -1.7    89.0 |  -0.23  0.822 |     .
                            |                                  |               |
access_extensionservices  U | .57778   .36283     44.0         |   4.05  0.000 |     .
                          M | .57423   .63585    -12.6    71.3 |  -1.69  0.192 |     .
                            |                                  |               |
------------------------------------------------------------------------------------------
* if variance ratio outside [0.81; 1.23] for U and [0.81; 1.23] for M

-----------------------------------------------------------------------------------
 Sample     | Ps R2   LR chi2   p>chi2   MeanBias   MedBias      B      R     %Var
```

```
-----------+-----------------------------------------------------------------
 Unmatched | 0.114     59.25    0.000     21.1      19.9      84.7*   0.82     80
 Matched   | 0.023     22.30    0.222      8.8       5.8      35.5*   1.55     20
-----------------------------------------------------------------------------
* if B>25%, R outside [0.5; 2]

. psmatch2 mechanization gender2 maritalstatus2 age education household_size farming_experience
livetsock_ownership main_occup
> ation2 totalincome access_credit access_extensionservice, outcome ( HFCSCORE )  kernel common

Probit regression                               Number of obs     =        473
                                                LR chi2(11)       =      59.25
                                                Prob > chi2       =     0.0000
Log likelihood = -230.43638                     Pseudo R2         =     0.1139

------------------------------------------------------------------------------------------
           mechanization |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
                 gender2 |  -.1459255    .147193    -0.99   0.321    -.4344184    .1425675
          maritalstatus2 |   .5570981   .1882716     2.96   0.003     .1880926    .9261037
                     age |  -.1517819   .1193844    -1.27   0.204    -.3857709    .0822072
               education |  -.0098576   .0851443    -0.12   0.908    -.1767373    .1570222
          household_size |  -.0546669    .025541    -2.14   0.032    -.1047263   -.0046075
      farming_experience |   .0235294   .0082992     2.84   0.005     .0072632    .0397956
     livetsock_ownership |    .419192   .1507492     2.78   0.005     .1237291     .714655
        main_occupation2 |    .249286   .1826613     1.36   0.172    -.1087236    .6072956
             totalincome |   1.25e-06   6.13e-07     2.05   0.041     5.34e-08    2.46e-06
           access_credit |    -.04331   .1486239    -0.29   0.771    -.3346074    .2479874
access_extensionservices |   .6403023   .1492767     4.29   0.000     .3477254    .9328791
                   _cons |  -.2459072    .475752    -0.52   0.605    -1.178364    .6865497
------------------------------------------------------------------------------------------
----------------------------------------------------------------------------------------
        Variable     Sample |    Treated     Controls   Difference         S.E.   T-stat
----------------------------+-----------------------------------------------------------
        HFCSCORE  Unmatched | 56.3583333   45.8539823    10.504351   2.15747576     4.87
                        ATT | 56.2759104   46.7961945   9.47971585   2.82518668     3.36
----------------------------+-----------------------------------------------------------
Note: S.E. does not take into account that the propensity score is estimated.

 psmatch2: |   psmatch2: Common
 Treatment |        support
assignment | Off suppo  On suppor |     Total
-----------+----------------------+----------
 Untreated |         0        113 |       113
   Treated |         3        357 |       360
-----------+----------------------+----------
     Total |         3        470 |       473


. pstest, both

------------------------------------------------------------------------------------------
                  Unmatched |       Mean               %reduct |     t-test    |  V(T)/
Variable            Matched | Treated Control    %bias  |bias| |    t    p>|t| |  V(C)
----------------------------+----------------------------------+---------------+----------
gender2                   U | .53333   .52212      2.2         |   0.21  0.835 |     .
                          M | .53221   .63602    -20.7  -826.1 |  -2.83  0.105 |     .
                            |                                  |               |
maritalstatus2            U | .81944   .71681     24.4         |   2.37  0.018 |     .
                          M | .82073   .84734     -6.3    74.1 |  -0.95  0.340 |     .
                            |                                  |               |
age                       U | 2.2389   2.1593     10.8         |   1.01  0.314 |  0.94
                          M | 2.2381   2.2077      4.1    61.9 |   0.55  0.580 |  0.96
                            |                                  |               |
education                 U | 3.4083   3.4425     -3.5         |  -0.33  0.738 |  0.81*
                          M |  3.409   3.4644     -5.7   -62.3 |  -0.78  0.433 |  0.88
```

```
                            |                                  |                   |
household_size          U   | 5.1972   5.4513     -9.5         |  -0.84  0.401 |  1.42*
                        M   | 5.2045   5.6292    -15.8   -67.1 |  -2.07  0.390 |  1.28*
                            |                                  |                   |
farming_experience      U   | 17.858   14.186     32.6         |   2.86  0.004 |  1.59*
                        M   | 17.681   16.994      6.1    81.3 |   0.79  0.428 |  1.24*
                            |                                  |                   |
livetsock_ownership     U   | .73056   .53982     40.3         |   3.86  0.000 |      .
                        M   | .72829     .705      4.9    87.8 |   0.69  0.491 |      .
                            |                                  |                   |
main_occupation2        U   |   .825   .74336     19.9         |   1.92  0.056 |      .
                        M   | .82353   .84253     -4.6    76.7 |  -0.68  0.497 |      .
                            |                                  |                   |
totalincome             U   | 1.1e+05    74214     29.6         |   2.59  0.010 |  1.61*
                        M   | 1.1e+05    94944     10.1    66.0 |   1.19  0.233 |  0.69*
                            |                                  |                   |
access_credit           U   | .43889   .36283     15.5         |   1.43  0.154 |      .
                        M   | .43978   .46825     -5.8    62.6 |  -0.76  0.445 |      .
                            |                                  |                   |
access_extensionservices U  | .57778   .36283     44.0         |   4.05  0.000 |      .
                        M   | .57423   .64198    -13.9    68.5 |  -1.86  0.164 |      .
                            |                                  |                   |
-------------------------------------------------------------------------------------------
* if variance ratio outside [0.81; 1.23] for U and [0.81; 1.23] for M

-----------------------------------------------------------------------------------
 Sample     | Ps R2   LR chi2   p>chi2   MeanBias   MedBias      B      R     %Var
------------+----------------------------------------------------------------------
 Unmatched | 0.114     59.25    0.000      21.1       19.9     84.7*   0.82     80
 Matched   | 0.019     19.08    0.160       8.9        6.1     32.8*   1.79     60
-----------------------------------------------------------------------------------
* if B>25%, R outside [0.5; 2]

. rename _treated t

.
.
.
. mhbounds HFCSCORE, gamma (1 (0.05)2) treated( mechanization )

Mantel-Haenszel (1959) bounds for variable HFCSCORE

Gamma         Q_mh+     Q_mh-     p_mh+     p_mh-
-------------------------------------------------
    1              .         .         .         .
 1.05       -.054337  -.054337   .521667   .521667
  1.1       -.054337  -.054337   .521667   .521667
 1.15       -.054337  -.054337   .521667   .521667
  1.2              .  -.054337         .   .521667
 1.25       -.054337  -.054337   .521667   .521667
  1.3       -.054337  -.054337   .521667   .521667
 1.35       -.054337         .   .521667         .
  1.4       -.054337  -.054337   .521667   .521667
 1.45       -.054337  -.054337   .521667   .521667
  1.5       -.054337  -.054337   .521667   .521667
 1.55       -.054337         .   .521667         .
  1.6       -.054337  -.054337   .521667   .521667
 1.65       -.054337  -.054337   .521667   .521667
  1.7       -.054337         .   .521667         .
 1.75       -.054337         .   .521667         .
  1.8              .  -.054337         .   .521667
 1.85              .  -.054337         .   .521667
  1.9       -.054337  -.054337   .521667   .521667
 1.95       -.054337  -.054337   .521667   .521667
    2       -.054337  -.054337   .521667   .521667
```

```
Gamma : odds of differential assignment due to unobserved factors
Q_mh+ : Mantel-Haenszel statistic (assumption: overestimation of treatment effect)
Q_mh- : Mantel-Haenszel statistic (assumption: underestimation of treatment effect)
p_mh+ : significance level (assumption: overestimation of treatment effect)
p_mh- : significance level (assumption: underestimation of treatment effect)
```

OUTPUT 2: OBJECTIVE 2

```
. regress FIES3 ATLESTWODAITADOPT2 gender2 maritalstatus2 age education household_size
farming_experience livetsock_ownership ma
> in_occupation2 totalincome access_credit access_market access_extensionservice

      Source |       SS           df       MS      Number of obs   =       473
-------------+----------------------------------   F(13, 459)      =     13.98
       Model |   187.37072        13  14.4131323   Prob > F        =    0.0000
    Residual |  473.094397       459  1.03070675   R-squared       =    0.2837
-------------+----------------------------------   Adj R-squared   =    0.2634
       Total |  660.465116       472   1.3992905   Root MSE        =    1.0152

------------------------------------------------------------------------------------------
                   FIES3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
      ATLESTWODAITADOPT2 |   .4892046   .1054146     4.64   0.000     .2820496    .6963595
                 gender2 |   .1613497   .1023518     1.58   0.116    -.0397865    .3624858
          maritalstatus2 |  -.0433529   .1355804    -0.32   0.749    -.3097881    .2230823
                     age |  -.0681426   .0846077    -0.81   0.421    -.2344091     .098124
               education |   .1138207   .0589657     1.93   0.054    -.0020555    .2296969
          household_size |    .000845   .0181864     0.05   0.963     -.034894     .036584
      farming_experience |   .0227124   .0053435     4.25   0.000     .0122115    .0332132
     livetsock_ownership |   .1347733    .108962     1.24   0.217     -.079353    .3488996
        main_occupation2 |  -.9462141   .1338799    -7.07   0.000    -1.209308   -.6831206
             totalincome |    1.38e-06   3.91e-07     3.53   0.000     2.15e-06   6.10e-07
           access_credit |   .2453748   .1024905     2.39   0.017     .0439661    .4467835
           access_market |  -.0612244   .1569422    -0.39   0.697    -.3696387    .2471898
access_extensionservices |   .1611897   .1136706     1.42   0.157    -.0621895    .3845689
                   _cons |   1.910796   .3595877     5.31   0.000     1.204154    2.617438
------------------------------------------------------------------------------------------

.
. vif

    Variable |       VIF       1/VIF
-------------+----------------------
farming_ex~e |      1.88    0.531354
         age |      1.76    0.568808
access_ext~s |      1.48    0.676477
   education |      1.43    0.700883
maritalsta~2 |      1.38    0.727182
access_mar~t |      1.36    0.736849
main_occup~2 |      1.29    0.775984
ATLESTWODA~2 |      1.27    0.784563
 totalincome |      1.21    0.823102
     gender2 |      1.20    0.835177
household_~e |      1.19    0.840759
livetsock_~p |      1.18    0.850579
access_cre~t |      1.17    0.851188
-------------+----------------------
    Mean VIF |      1.37

.
. linktest

      Source |       SS           df       MS      Number of obs   =       473
```

```
-------------+----------------------------------   F(2, 470)       =     95.30
       Model |  190.567373         2  95.2836867   Prob > F        =    0.0000
    Residual |  469.897743       470  .999782432   R-squared       =    0.2885
-------------+----------------------------------   Adj R-squared   =    0.2855
       Total |  660.465116       472   1.3992905   Root MSE        =    .99989

------------------------------------------------------------------------------
       FIES3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   1.796147   .4511962     3.98   0.000     .9095354    2.682758
      _hatsq |  -.1722768   .0963455    -1.79   0.074    -.3615981    .0170445
       _cons |  -.8478015   .5018704    -1.69   0.092    -1.833989     .138386
------------------------------------------------------------------------------

.
. estat imtest

Cameron & Trivedi's decomposition of IM-test

---------------------------------------------------
              Source |       chi2     df      p
---------------------+-----------------------------
  Heteroskedasticity |     162.94     96    0.0000
            Skewness |      91.81     13    0.0000
            Kurtosis |      20.16      1    0.0000
---------------------+-----------------------------
               Total |     274.92    110    0.0000
---------------------------------------------------

.
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of FIES3

         chi2(1)      =     7.21
         Prob > chi2  =   0.0072

.
. ovtest

Ramsey RESET test using powers of the fitted values of FIES3
       Ho:  model has no omitted variables
                 F(3, 456) =      2.20
                  Prob > F =      0.0871

.
. ologit FIES3 ATLESTWODAITADOPT2 gender2 maritalstatus2 age education household_size
farming_experience livetsock_ownership mai
> n_occupation2 totalincome access_credit access_market access_extensionservice

Iteration 0:   log likelihood = -621.39734
Iteration 1:   log likelihood = -544.02624
Iteration 2:   log likelihood = -542.92437
Iteration 3:   log likelihood = -542.92098
Iteration 4:   log likelihood = -542.92098

Ordered logistic regression                     Number of obs     =        473
                                                LR chi2(13)       =     156.95
                                                Prob > chi2       =     0.0000
Log likelihood = -542.92098                     Pseudo R2         =     0.1263

------------------------------------------------------------------------------------------
                   FIES3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
```

```
      ATLESTWODAITADOPT2 |   .9566407   .2022123     4.73   0.000     .5603119    1.352969
                 gender2 |   .3517142   .1971893     1.78   0.074    -.0347697    .7381981
          maritalstatus2 |   -.115458   .2643048    -0.44   0.662    -.6334858    .4025699
                     age |  -.0927809   .1672311    -0.55   0.579    -.4205479    .2349861
               education |   .2022056   .1127233     1.79   0.073    -.0187279    .4231391
          household_size |   .0144794   .0338054     0.43   0.668    -.0517781    .0807368
      farming_experience |   .0401042   .0104574     3.84   0.000     .0196081    .0606002
     livetsock_ownership |   .2596569   .2081425     1.25   0.212    -.1482949    .6676087
         main_occupation2 |   1.586113   .2611538     6.07   0.000     2.097965    1.074261
             totalincome |   3.20e-06   9.25e-07     3.46   0.001     5.01e-06    1.39e-06
           access_credit |   .3660191   .1980351     1.85   0.065    -.0221225    .7541606
           access_market |  -.1848416   .3017847    -0.61   0.540    -.7763288    .4066455
access_extensionservices |   .3305374   .2241357     1.47   0.140    -.1087606    .7698353
-------------------------+----------------------------------------------------------------
                   /cut1 |   .1717163   .6960349                     -1.192487     1.53592
                   /cut2 |   1.257196   .7000152                     -.1148082    2.629201
                   /cut3 |   2.259093    .704168                      .8789488    3.639237
------------------------------------------------------------------------------------------

.
```

OUTPUT 3: OBJECTIVE 3

```
. regress HDDs SAIPs2 gender2 maritalstatus2 age education household_size farming_experience l
> ivetsock_ownership main_occupation2 totalincome access_credit access_market access_extension
> service

      Source |       SS           df       MS      Number of obs   =       431
-------------+----------------------------------   F(13, 417)      =     10.45
       Model |  663.519138        13  51.0399337   Prob > F        =    0.0000
    Residual |  2036.66184       417  4.88408114   R-squared       =    0.2457
-------------+----------------------------------   Adj R-squared   =    0.2222
       Total |  2700.18097       430  6.27949064   Root MSE        =      2.21

------------------------------------------------------------------------------------------
                    HDDs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
                  SAIPs2 |   1.068983    .266088     4.02   0.000     .5459424    1.592024
                 gender2 |   .2914394   .2343766     1.24   0.214    -.1692676    .7521463
          maritalstatus2 |   .5517846   .3043794     1.81   0.071    -.0465247    1.150094
                     age |   .0808487   .1910985     0.42   0.672    -.2947877    .4564851
               education |   .2825551   .1336579     2.11   0.035     .0198279    .5452824
          household_size |  -.1004923   .0412758    -2.43   0.015    -.1816269   -.0193578
      farming_experience |   .0237644   .0121661     1.95   0.051    -.0001502     .047679
     livetsock_ownership |   .6823662   .2467703     2.77   0.006     .1972974    1.167435
        main_occupation2 |  -.0730274   .2974475    -0.25   0.806    -.6577108     .511656
             totalincome |   3.10e-06   8.53e-07     3.63   0.000     1.42e-06    4.78e-06
           access_credit |   .2312998   .2335442     0.99   0.323    -.2277709    .6903704
           access_market |   .9740406   .3472676     2.80   0.005     .2914273    1.656654
access_extensionservices |   .7595707   .2621126     2.90   0.004     .2443441    1.274797
                   _cons |   3.126182   .7706166     4.06   0.000     1.611405    4.640959
------------------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
farming_ex~e |      1.91    0.522615
         age |      1.73    0.578140
access_ext~s |      1.51    0.660367
   education |      1.46    0.685791
access_mar~t |      1.38    0.724594
maritalsta~2 |      1.37    0.728521
```

```
main_occup~2 |      1.28    0.781670
household_~e |      1.21    0.825459
     gender2 |      1.21    0.827121
      SAIPs2 |      1.19    0.841999
 totalincome |      1.18    0.846073
access_cre~t |      1.17    0.852910
livetsock_~p |      1.17    0.858235
-------------+----------------------
    Mean VIF |      1.37

. linktest

      Source |       SS           df       MS      Number of obs   =       431
-------------+----------------------------------   F(2, 428)       =     71.33
       Model |  675.015499         2  337.50775    Prob > F        =    0.0000
    Residual |  2025.16548       428  4.73169504   R-squared       =    0.2500
-------------+----------------------------------   Adj R-squared   =    0.2465
       Total |  2700.18097       430  6.27949064   Root MSE        =    2.1752

------------------------------------------------------------------------------
        HDDs |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   .0511708   .6145469     0.08   0.934    -1.156735    1.259076
      _hatsq |   .0672287   .0431303     1.56   0.120    -.0175448    .1520021
       _cons |   3.244314   2.167729     1.50   0.135    -1.016404    7.505033
------------------------------------------------------------------------------

. estat imtest

Cameron & Trivedi's decomposition of IM-test

---------------------------------------------------
              Source |       chi2     df      p
---------------------+-----------------------------
  Heteroskedasticity |     136.28     96    0.0043
            Skewness |      39.50     13    0.0002
            Kurtosis |       0.02      1    0.8915
---------------------+-----------------------------
               Total |     175.80    110    0.0001
---------------------------------------------------

. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of HDDs

         chi2(1)      =     0.47
         Prob > chi2  =   0.4941

. ovtest

Ramsey RESET test using powers of the fitted values of HDDs
       Ho:  model has no omitted variables
                 F(3, 414) =      3.17
                  Prob > F =      0.0243

. poisson HDDs SAIPs2 gender2 maritalstatus2 age education household_size farming_experience l
> ivetsock_ownership main_occupation2 totalincome access_credit access_market access_extension
> service, vce(robust)

Iteration 0:   log pseudolikelihood = -957.83981
Iteration 1:   log pseudolikelihood = -957.83969
Iteration 2:   log pseudolikelihood = -957.83969

Poisson regression                              Number of obs     =        431
```

```
                                                Wald chi2(13)     =     130.22
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -957.83969               Pseudo R2         =     0.0471

------------------------------------------------------------------------------------------
                          |               Robust
                     HDDs |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------------+---------------------------------------------------------------
                   SAIPs2 |   .1394263   .0361738     3.85   0.000     .0685271    .2103256
                  gender2 |   .0424271   .0313986     1.35   0.177     -.019113    .1039672
           maritalstatus2 |   .0860181   .0428381     2.01   0.045     .0020569    .1699793
                      age |   .0105161   .0256601     0.41   0.682    -.0397767     .060809
                education |   .0393374   .0184155     2.14   0.033     .0032437    .0754312
           household_size |  -.0154248    .006667    -2.31   0.021    -.0284919   -.0023577
       farming_experience |   .0034885    .001613     2.16   0.031     .0003271    .0066498
      livetsock_ownership |   .1021565   .0345041     2.96   0.003     .0345296    .1697833
         main_occupation2 |  -.0130661   .0356716    -0.37   0.714    -.0829812     .056849
              totalincome |   3.58e-07   9.74e-08     3.68   0.000     1.67e-07    5.49e-07
            access_credit |   .0348041   .0304969     1.14   0.254    -.0249688     .094577
            access_market |   .1827087   .0612828     2.98   0.003     .0625967    .3028207
access_extensionservices |   .1002821   .0391178     2.56   0.010     .0236125    .1769516
                    _cons |   1.358097   .1085707    12.51   0.000     1.145303    1.570892
------------------------------------------------------------------------------------------

. estatic
command estatic is unrecognized
r(199);

. estat ic

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |        431 -1005.204  -957.8397      14    1943.679   2000.605
-----------------------------------------------------------------------------
               Note: N=Obs used in calculating BIC; see [R] BIC note.

. estatgof
command estatgof is unrecognized
r(199);

. estat gof

         Deviance goodness-of-fit =  301.7341
         Prob > chi2(417)         =    1.0000

         Pearson goodness-of-fit  =  293.0631
         Prob > chi2(417)         =    1.0000
```

APPENDIX VII: SAMPLING FRAME

No	Name of Farmers
1	Rose Akoth
2	Jane Adoyo
3	Cynthia Okundi
4	Jackline Mboya
5	THOMAS OYUKE
6	Victor Omondi
7	Mbai Wilfred
8	Bernard Wasonga
9	Jared Oigo
10	Moline Ochieng
11	Isaiah Ambogo
12	Damris Odira
13	Charles Onyango
14	Melvine Anyango
15	Roseline Atieno Odero
16	Jacob Oyare
17	JAEL AKOTH MBAI
18	Daniel Ombok
19	Jackline Kakyo
20	Roseline Ogembo
21	Dickens Omondi Gilly
22	Antoninah Awuor
23	John Ogero
24	Kennedy Otieno
25	Margaret Okebe
26	Irine Ayara
27	Johanes Oduka
28	John Ongaro

29	Maurice Odhiambo Akumu
30	Lencer Achieng
31	PHILIP OLUOCH
32	Jane Anyango
33	Joan Adhiambo Ooko
34	Joram Ogolla
35	Caroline Auma
36	Mary Gorrety Auma
37	Lilian Kamonya
38	George Oguda
39	Silvya Anana
40	Joseph Odoyo
41	Kenneth Ooko
42	Elly Benson
43	Wilson Ojwang'
44	Philip Atito
45	Evance Ouya
46	Erick Onyango
47	Veronica Anyanga
48	Killion Ouma
49	ODONGO NAMAN
50	Fredrick Omondi
51	Joseph Odhiambo
52	Elijah Gumba
53	Rose Akinyi
54	Stacy Awuor
55	Josinta Atieno
56	Sellah Ayaga
57	Silvia Achieng
58	Theodore Akinyi Sure

59	Jackline Atieno
60	Ongwela Everlyne Achieng
61	Jane Osiro
62	Caroline Adoyo Aguko
63	Kennedy Ochieng Mumbo
64	George Ngala
65	Moses Onguru
66	Florence Akinyi
67	Rose Okeyo
68	Kevin Owiti
69	William Odhiambo Opiyo
70	Cynthia Achieng
71	George Oyier
72	Joseph Oluoch
73	Perez Atieno
74	Ben Omondi
75	John Akumu
76	Emanuel Ouko
77	Brian Odhiambo
78	John Onyango Aoko
79	Phillip Odero
80	Hellen Akinyi
81	Alphonce Ouru
82	Mercy Akinyi
83	Dlamas Olum
84	Irine Adhiambo Ayara
85	Judith Achieng'
86	Eveline Atieno
87	Florence Akinyi
88	OMBURO BENARD

89	LINDAH OCHIENG
90	Hellen Aoko Agunga
91	George Omondi
92	JANE ATIENO NYAKWAKA
93	John Otieno
94	Mercy Otieno
95	Caren Akinyi
96	Siprose Anyango Ogwenya
97	Sharon Awuor
98	Elizabeth Akinyi
99	Mary Oloo
100	Janet Akoth
101	Margaret Ojunju
102	Sakina Anudo
103	Peter Obudho
104	Elizabeth Agwa
105	Rose Atieno
106	Jane Atieno
107	Mary Ocholla
108	Samuel Obado Omito
109	Richard Omoro Onyango
110	Jacob Adero Otieno
111	Jedidah Atieno Aoch
112	Tom Mboya
113	Kennedy Osano
114	Jane Atieno
115	John Otieno
116	George Omondi
117	Sheila Awuor Otieno
118	Grace Ayatta

119	Thomas Tembe
120	Ludia Akongo
121	Killion Owuore
122	Sarah Omondi
123	Philip Ongonge
124	Monica Yoto
125	Elisha Akongo
126	Peter Aloo
127	Charles Oniala
128	Peter Okomo
129	Ironed Omollo
130	Nancy Atieno
131	Evance Odemba
132	Teresa Atieno Anoyo
133	Maureen Atieno Oyoo
134	FULDA ANYANGO
135	Catherine Adhiambo Aringo
136	Marry Akinyi
137	Millicent Oyier
138	Margret Atieno
139	Elizabeth Agwa
140	Rose Atieno
141	Jane Atieno
142	Mary Ocholla
143	Careen Okomo
144	Caroline Odiko
145	Monica Ochola
146	John Amimo
147	Eunice Okello
148	Esther Mboya

149	Tobias Okello
150	Hellen Oremo
151	Millicent Okundi
152	Maxwell Onsando
153	Erick Opuk
154	Janes Okinyi
155	Caroline Atieno
156	Charles Owino
157	Bonphace Kialo
158	Moses Owuor
159	Lilian Awino
160	Caren Anyango
161	Dona Irine
162	Musa Dengu
163	Calvince Onyango
164	Samuel Maria Ngwala
165	Charlie's Otieno Omito
166	Nollah Anyango
167	George Ochieng
168	Jane Owire
169	Steve Arunga
170	Lilian Akoth
171	Viola Awuor
172	Tom Ogira
173	Elijah Outa
174	Hellen Akinyi
175	Levinda Ouma
176	Rose Achieng
177	Ruth Akinyi Gumba
178	Dorcus Odero

179	Magret Agola Achola
180	Dinah Otieno
181	Dennis Opiyo
182	Gabriel Opiyo
183	Grace Anyango
184	Beatrice Atieno Oloo
185	Rebecca Abonga
186	Rose Auma
187	Juma Owino
188	Pamela Odira
189	Kenneth Ochieng'
190	Consolata Obado
191	Edward Mbai
192	Peter Obado
193	Obisa Bunde
194	Odero Abanga
195	Odero Ayalo
196	Mary Otieno
197	Maxwell Ouma
198	Margaret Awuor
199	Pheobe Wisa
200	Alfred Okeyo
201	Elizabeth Oloo
202	Mary Ngicho
203	Tonny Ouno
204	Dorina Wajero
205	Alice Adhiambo
206	Michael Wajero
207	Eliver Mboya
208	Elmards Osiro Akech

209	Monicah Alele
210	Hellen Adhiambo
211	Peninah Adongo
212	George Origa
213	John Oganga
214	George Ngala
215	Molena Aguko
216	Ouno Origao
217	Victor Ochieng
218	Margaret Adongo
219	Dison Ouma Odemba
220	Bella Chaha
221	Bob Oyoo
222	Johnson Joel
223	Nicholas Odhiambo
224	Walter Ogada
225	Wickliffe Ogweno
226	Charles Mwaya
227	Joshua Ouko
228	Colince Opiyo
229	Bernard Oyugi
230	Evance Okinyi
231	Perez Anyango Omollo
232	Calvince Atito
233	Janet Adhiambo
234	Pauline Oyieke
235	Clifford Omondi
236	Penina Aol
237	Giorgio Armani
238	Grace Nyangodi

239	Nancy Akoth
240	George Oyoo
241	John Oyugi
242	Beatrice Atieno
243	Mary Odago
244	Rashid Ochieng
245	Leonida Oketch
246	Vera Adhiambo
247	Antony Odhiambo
248	George Odhiambo
249	Wilfred Ajwang
250	Peres Aketch
251	Pamela Adoyo Otumba
252	Debora Onyango
253	Briton Ouma
254	Eunice Akoth
255	John Otieno
256	Joshua Were
257	Richard Odoyo
258	Doline Otieno
259	Maurine Anyango
260	Clement Okal
261	Brighton Odhiambo
262	Maureen Achieng
263	Moses Ouru
264	Sila Ogolla
265	Emequlate Adhiambo
266	Aska Kwamboka
267	Benard Odhiambo
268	Tony Otieno

269	Dismas Oloo
270	Mary Adhiambo
271	Silipa A Wino
272	James Ogola
273	Underson Oluoch
274	Peter Obonyo
275	Caren Kawala
276	Duncan Otieno
277	Peres Atieno
278	Stella Awino
279	Molly Anyango
280	Albert Owuor
281	Daniel Ogembo
282	Bob Adero
283	Joelogutu
284	Judith Odhiambo
285	Julita Anyango Oswago
286	Lencer Atieno Osoro
287	Charlies Mbori
288	Lawrence Owino
289	Nyabute Horizon
290	John Mwai Kanga
291	Richard Abich
292	Joshua Onyango
293	James Owuonda
294	Tabitha Chacha
295	Richard Wasonga
296	Tyrus Ochieng
297	Violet Otieno
298	Castro Cecil

299	Emily Odhiambo
300	Kelly Daniel
301	Sincy Mandela
302	Evelyn Alango
303	Pamela Okelo
304	George Oketch
305	Phoebe Atieno
306	Tabitha Atieno
307	Rose Akumu
308	Lawrence Ouma
309	Fesal Oketch
310	Joyce Atieno
311	Ben Oluoch
312	Caleb Okello
313	Franklin Omondi
314	Bonface Otieno
315	Evans Oyieke
316	Esther Omollo
317	Joseph Omolo
318	Maryveline Apondi
319	Millicent Kibogo
320	Mercy Akinyi
321	Joseph Omollo
322	Tom Ochieng
323	Elijah Ajuoga
324	Kennedy Ochieng
325	Grace Dengu
326	Ruth Ogola
327	Erick Odero
328	Gordon Adongo

329	John Okinyi
330	Edwin Jabuyap
331	Harrison Omondi
332	Robert Ochieng
333	Judith Adundo
334	Nelson Koth Odalo
335	Cassim Onyango
336	Waida Asman
337	Samwel Otieno
338	Nillo Ouma
339	David Wasonga
340	Anteninah Atieno
341	Alfred Opiyo
342	Molly Akinyi
343	Hellen Airo
344	Tabitha Achieng Onena
345	Thomas Akiru Nungo
346	Jocinta Auma
347	Nelson Chacha
348	Tabitha Achieng Oliech
349	Calvince Ochieng
350	Simon Odiwuor Onyango
351	Ernest Otedo
352	Daniel Otieno
353	Wickliffe Ouma
354	Elly Odhiambo
355	Rafael Otieno
356	Calvince Omondi
357	Roseline Okode
358	Joan Achieng

359	Erick Omondi
360	Jeremiah Obunga
361	Daniel Andrew
362	Nora Anyango Odhiambo
363	Elizabeth Achieng
364	Jackline Adhiambo Owino
365	Millicent Odalo
366	Rose Atieno
367	Grace Oduya
368	Rose Akinyi
369	Gafaffi Boma
370	Tobias Juma Ondenge
371	Peter Wajero
372	Kennedy Rabach
373	Hillary Obwaga
374	Esther Muga
375	Kennedy Loch
376	John Orenje
377	Caleb Ndinya
378	Sarah Atieno Odero
379	Enoch Arieya
380	Elly Abiero
381	Robbert Saka
382	Nick Ogoye
383	Salmon Ogembo
384	Peter Ocholah
385	Becky Atieno
386	Grace Akinyi
387	Collins Okumu
388	Veronica Aoko

389	Rolex Owuor
390	Rebecca Anyango
391	Violet Akinyi Otieno
392	Judith Auma
393	Janet Adhiambo
394	Yuda Odongo
395	Tukiko Alomo
396	Sabina Rume
397	Peter Midamba
398	Rosemary Adimo
399	Victor Obondo
400	Kenneth Odhiambo
401	Peter Amollo
402	Lukas Okello Ndiege
403	Hellen Adhiambo Nyakundi
404	Richard Otieno Odero
405	Maurice Onyango
406	David Odhiambo
407	Justine Achieng Otieno
408	Nicodemus Ogutu
409	Damaris Akinyi
410	Rosa Ondigo
411	Meresa Otieno
412	Pamela Anyango
413	Willis Otieno
414	Josh Anyango
415	John Oliech
416	Martha Nyatenya
417	Nancy Onditi
418	Jenifer Ogal

419	Keziah Akoth
420	Timothy Otieno
421	Elekiah Okumu
422	Daniel Dianga
423	Pamela Akoth
424	Stephen Otieno
425	Joseph Opar
426	Sunday Atieno
427	Agness Atieno
428	Mactelda Ogodo
429	David Ongola
430	Christine Odero
431	James Adero
432	Siprina Ojwang
433	Benard Okeyo
434	Jared Otieno Ojwang
435	Lilian Ouma
436	Samson Olela
437	Simeon Opiyo
438	Beatrice Akoth
439	Elizabeth Akinyi
440	Sharon Atieno
441	Penina Aluoch
442	Justine Otieno
443	Victor Mboya
444	Tobias Nyagowa
445	Fares Ogada
446	Mollen Juma
447	Fredrick Ochieng
448	Margaret Ogweno

449	Sheryl Aketch
450	Godfrey Okebe
451	Rose Okebe
452	Phoebe Akoth
453	Emmanuel Etembe
454	Tifina Kerubo
455	Siprose Adhiambo
456	Conslata Adhiambo
457	Bonface Olouch
458	Jafeth Awino
459	Vincent Oluoch
460	Joshua Otieno Ombok
461	Everline Akoth
462	Hellen Adhiambo
463	Lydia Awuor
464	Samwuel Okumu
465	Saline Auma
466	Jacob Omolo
467	Velma Akoth
468	Leah Anyango
469	Lilian Atieno
470	Mary Akeyo
471	Meshack Ogola
472	Simon Oduor
473	Pamela Amolo
474	Simon Orwa
475	David Ooko
476	Dalmas Otieno
477	Sabina Oyieke
478	Rashid Ayoma

APPENDIX VIII: MAP OF STUDY AREA

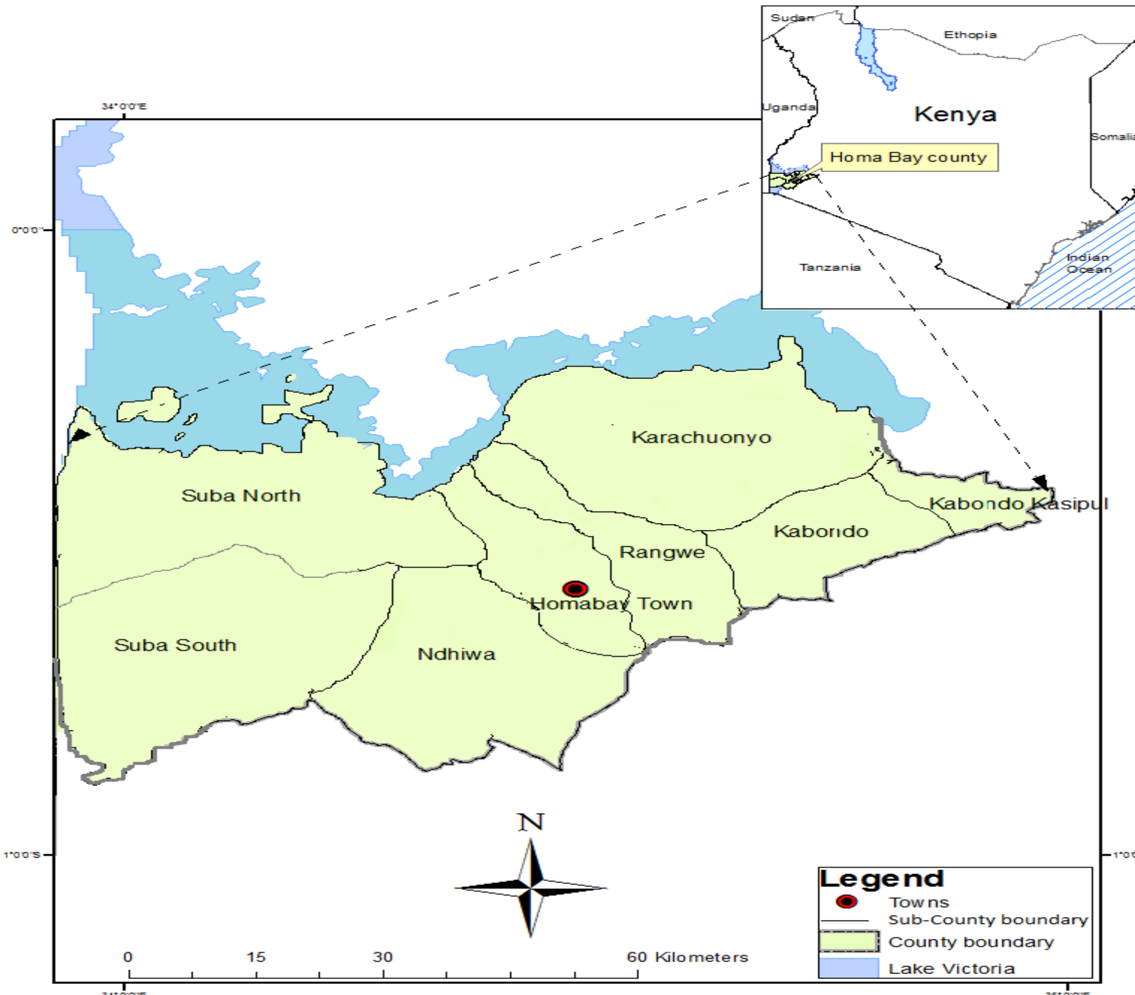

Figure 0-1: Homa Bay County map, showing study area ArcGIS generated, 2024