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ANALYSIS OF FACTORS INFLUENCING THE ADOPTION OF GOOD AGRICULTURAL PRACTICES (GAPS) AMONG SMALLHOLDER AVOCADO FARMERS IN MURANGA COUNTY, KENYA

BY

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REG NO: 202612

DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF MANAGEMENT IN AGRIBUSINESS, STRATHMORE UNIVERSITY

JUNE, 2026

DECLARATION

Student's Declaration

I declare that this thesis dissertation is my original work and has not been submitted for the award of a degree at any other University. No part of this dissertation may be reproduced without my written consent or that of Strathmore University.

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Approval by the Supervisor

This dissertation has been submitted for examination with my approval as the University Supervisor.

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Signature: __________________________ **Date:** 20/6/2026

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ABSTRACT

Kenya's avocado sector is one of the fastest-growing in Africa, yet a persistent gap exists between production volumes and export performance, with less than 20% of output consistently reaching international markets. Compliance with Good Agricultural Practices (GAPs) is a critical precondition for export market access, particularly given the stringent sanitary and phytosanitary (SPS) requirements imposed by markets such as the European Union and China. Despite widespread promotion of GAPs frameworks, adoption among smallholder farmers in Murang'a County, Kenya's leading avocado-producing region, remains uneven and inadequately understood. This study examined the influence of farm size, training, and contract farming with exporter companies on the adoption of GAPs across pre-harvest, harvest, and post-harvest production stages. The study used secondary data from a cross-sectional survey, with structured questionnaires administered digitally via KoboToolbox to 698 smallholder avocado farmers in Murang'a County, Kenya. Multi-stage purposive and random sampling were used to select respondents across key sub-counties. GAPs adoption was disaggregated into three binary outcomes: pre-harvest, harvest, and post-harvest practices. A Multivariate Probit (MVP) model was applied to jointly estimate adoption decisions across the three stages while accounting for inter-practice correlations and cluster-robust standard errors. Farm size exerted a positive effect only on pre-harvest GAPs adoption ($\beta = 0.186$, $p < 0.10$), with pre-harvest adopters operating on significantly smaller avocado areas than non-adopters (1.18 vs. 1.48 acres, $p = 0.011$). Training was a significant predictor of pre-harvest adoption ($\beta = 0.514$, $p < 0.05$) but had no significant effect on harvest or post-harvest adoption. Contract farming strongly influenced both pre-harvest ($\beta = 1.505$, $p < 0.01$) and post-harvest adoption ($\beta = 0.777$, $p < 0.05$). High GAPs adopters exported a significantly greater proportion of their harvest and achieved higher shares of Grade 1 produce than low GAPs adopters. The findings challenge the conventional assumption that larger farms are more likely to adopt GAPs, demonstrating instead that institutional factors, particularly contract farming and targeted training, are more powerful determinants of compliance. Policy should prioritize expanding contract farming arrangements, broadening training content to cover downstream practices, and strengthening public extension services across the avocado value chain in Kenya.

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DEDICATION

I dedicate this thesis to my beloved parents, David Njoka and Nancy Njoka, for their unwavering love, sacrifices, guidance, encouragement, and steadfast support throughout my academic journey. Your hard work, values, and belief in my potential have been a constant source of inspiration and motivation. This achievement is a reflection of your dedication and the strong foundation you have provided for me. I am deeply grateful for your prayers, patience, and countless sacrifices that made this accomplishment possible.

May this work stand as a testament to your enduring influence and the immeasurable role you have played in shaping my life.

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LIST OF ACRONYMS AND ABBREVIATIONS

AGRA	Alliance for a Green Revolution in Africa
DoI	Diffusion of Innovations
ESR	Endogenous Switching Regression
FAO	Food and Agriculture Organization of the United Nations
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
GAPs	Good Agricultural Practices
GDP	Gross Domestic Product
GoK	Government of Kenya
HDI	Human Development Index
ICT	Information and Communication Technology
IPM	Integrated Pest Management
ITC	International Trade Centre
KALRO	Kenya Agricultural and Livestock Research Organization
KEBS	Kenya Bureau of Standards
KEPHIS	Kenya Plant Health Inspectorate Service
KMO	Kaiser-Meyer-Olkin (Measure of Sampling Adequacy)
KNBS	Kenya National Bureau of Statistics
NACOSTI	National Commission for Science, Technology, and Innovation
RUT	Random Utility Theory
SDGs	Sustainable Development Goals
SSA	Sub-Saharan Africa
UN	United Nations
UNCTAD	United Nations Conference on Trade and Development
USDA	United States Department of Agriculture

WAO	World Avocado Organization
WB	World Bank
WTO	World Trade Organization

DEFINITION OF TERMS

Good Agricultural Practices (GAPs): Internationally recognized guidelines and standards ensure the safe, sustainable, and traceable production of agricultural commodities. In this study, GAPs include pre-harvest practices like integrated pest management and pesticide application; harvest practices such as hand-picking and using clean tools; and post-harvest practices like sorting, crate use, and adherence to pesticide withdrawal periods.

GAPs Adoption: A smallholder avocado farmer's decision to adopt one or more recommended Good Agricultural Practice techniques at any stage, pre-harvest, harvest, or post-harvest, is considered. In this study, adoption is recorded as a binary variable (1 = Yes, 0 = No) for each practice, and composite adoption scores are calculated based on these responses.

Smallholder Farmer: A small-scale farmer working on plots usually less than two acres, primarily using family labor. Their production aims at both subsistence and selling in markets. In this study, the focus is on smallholder avocado farmers in Murang'a County.

Contract Farming: A formal agreement between an avocado farmer and an exporter or buyer that outlines the supply terms, such as quantity, quality standards, price, and occasionally inputs or technical support. In this study, contract farming is represented as a dummy variable (1 = has a contract, 0 = no contract).

Sanitary and Phytosanitary (SPS) Standards: Mandatory regulatory requirements imposed by importing countries aim to safeguard human, animal, and plant health from risks related to pests, diseases, or food contaminants. In Kenya's avocado export industry, SPS compliance involves adhering to pesticide residue limits, dry matter standards, and traceability criteria established by markets like the European Union and China.

GlobalG.A.P. Certification: A globally recognized voluntary private standard created by producers, certification bodies, and retailers to guarantee the safe, sustainable, and socially responsible production of agricultural products. For Kenyan avocado farmers, achieving GlobalG.A.P. certification is essential for entering premium export markets in Europe and Asia.

Integrated Pest Management (IPM): A sustainable pest control approach integrates biological, cultural, physical, and chemical methods to reduce economic loss and lessen environmental effects. In avocado farming, IPM involves bi-weekly monitoring of quarantine pests like fruit fly and False Codling Moth, applying approved pesticides at proper dosages, and implementing biological control measures.

Post-harvest Loss: This study characterizes post-harvest loss as the share of the total avocado harvest that is discarded or becomes unsellable, due to deterioration in quantity and quality during handling, storage, packaging, or pre-cooling.

Export Share: This figure represents the percentage of a farmer's total avocado harvest sold to international markets. It acts as a crucial indicator of market access and export competitiveness and is utilized in this study to evaluate how GAPs adoption influences market performance outcomes.

Multivariate Probit (MVP) Model: This econometric model estimates the likelihood of multiple correlated binary outcomes simultaneously, permitting the error terms across different adoption equations to be freely correlated. In this study, the MVP model is used to jointly analyze GAPs adoption decisions across pre-harvest, harvest, and post-harvest stages, effectively capturing the complementarities and interdependencies among these adoption choices.

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CHAPTER 1: INTRODUCTION

1.1 Background information

Avocado is among the fastest-growing fruit crops worldwide, with global production hitting approximately 10.5 million metric tons in 2023/2024 (FAOSTAT, 2025) and exports totalling nearly USD 9.7 billion (FAOSTAT, 2025; OECD & FAO, 2025). This reflects strong and increasing international demand for the crop. However, export competitiveness depends on meeting international standards. These include frameworks like OECD guidelines and private schemes such as Global-GAPs, which regulate food safety, traceability, and pest control (OECD, 2020). Producers who fail to meet these requirements are excluded from the most profitable markets, regardless of how much they produce.

Kenya is the top producer of avocados in Africa and is among the largest exporters on the continent, with production increasing from 234,000 tonnes in 2018 to more than 542,000 tonnes in 2023 (Muita *et al.,* 2025; Statista, 2024), reaching about 848,100 tonnes valued at KSh 29.5 billion in 2024 (USDA, 2025a). Yet Kenya exported only about 123,000 tonnes in 2023 (Shivachi *et al.,* 2023; USDA, 2025a). A small portion of the total output, indicating that the majority of national production does not reach the higher-value export markets accessible to Good Agricultural Practices (GAPs)- compliant produce. This ongoing disparity between production volume and export share constitutes the primary issue motivating this study, which is significantly influenced by inconsistent compliance with GAPs and Sanitary and Phytosanitary Standards (SPSs) requirements among producers (Muita *et al.,* 2025).

Murang'a is the top county in Kenya for avocado production among the major growing regions (Food Business Middle East and Africa, 2023; Stats Kenya, 2025), making it the most appropriate area of study for understanding why GAPs adoption stays low, despite the county's key role in national production. In the county, schemes like GlobalG.A.P. and similar certifications that focus on integrated pest management, traceability, and pesticide residue limits have been widely promoted. For example, through the Netherlands Trust Fund (NTF) III Kenya Avocado Project, over 300 smallholder farmers in Murang'a achieved GlobalG.A.P. certification in 2017, enabling them to access European markets directly (International Trade Centre [ITC], 2017).

The certification process entailed connecting farmer groups with exporters, providing training on GLOBALG.A.P. audit standards, and developing quality management systems. Exporters also invested in supporting infrastructure like collection centres and sanitation facilities (AFA-HCD, 2024). Certified farmers reportedly earned as much as double the income compared to those selling via informal middleman-dominated channels (Johnny *et al.,* 2019). Despite benefits and support from government, NGOs, and exporters, smallholder GAPs adoption in Murang'a remains uneven due to certification costs, limited extension services, and infrastructure gaps (The International Food Policy Research Institute [IFPRI], 2020). While the advantages of GAPs adoption are well documented and success stories like Murang'a's 2017 certification showcase potential achievements, most current research concentrates on overall output, income impacts, or particular elements such as post-harvest losses.

Without breaking down GAPs adoption by production stage (pre-harvest, harvest, post-harvest) or systematically identifying which farm-level and institutional factors such as farm size, training, and contract farming with exporters influence adoption at each stage (Muita *et al.,* 2025). Recent export rejections linked to quality issues in Kenya underscore the urgency of closing this gap (Ramírez-Gil *et al.,* 2019). As a result, policymakers, exporters, and extension services lack tailored empirical guidance for closing Kenya's production-to-export gap at different stages. This study fills that gap by examining how farm size, training, and contract farming influences the adoption of Good Agricultural Practices during pre-harvest, harvest, and post-harvest stages among smallholder avocado farmers in Murang'a County, Kenya.

1.1.1 Independent variables and their operationalization

This study examines three factors affecting GAPs adoption among smallholder avocado farmers: farm size, access to training, and involvement in contract farming. Kenya leads in avocado production and exports, and regional and global competitiveness hinges on compliance with safety and quality standards, making these variables particularly relevant (USDA, 2025b). Farm size is expressed in hectares (or acres) of avocado cultivation. Because smallholder farms in East Africa tend to be small, farm size is a crucial explanatory variable, as the scale influences a farmer's ability to invest in and comply with GAPs requirements. (Chelang'a *et al.,* 2021).

Access to training or extension services is measured as a binary indicator (1 = has received training, 0 = has not), reflecting evidence that exposure to training significantly influences compliance with GLOBALG.A.P. and similar standards among smallholder horticultural producers (Chelang'a *et al.,* 2021). Contract farming is measured as a binary indicator (1 = has a contract with an exporter or buyer, 0 = does not), given that vertical coordination through contracts shapes farmers' quality-improvement behaviour and market participation in Kenya's avocado sector (Johnny *et al.,* 2019). Together, these three variables allow the study to explore how farm size, training, and contract farming influences GAPs adoption, as well as how these factors influence smallholder performance in Kenya's avocado value chain.

1.1.2 Dependent and outcome variables and their operationalization

The main dependent variable is GAPs adoption, measured in two ways: (i) as a binary indicator (1 = adopter, 0 = non-adopter) for each of the three production stages pre-harvest, harvest, and post-harvest and (ii) as a composite compliance index. This index covers practices like soil and fertilizer management, pest and disease control, hygiene and traceability, harvesting, and post-harvest handling, in line with international GAPs standards (Chelang'a *et al.,* 2021). In addition to GAPs adoption, the study examines market orientation and performance outcomes to characterize farmers and assess the downstream effects of adoption. Yield (kg per hectare or avocados per tree) indicates farm productivity by showing if GAPs-related orchard, pest, and soil management practices lead to higher output. Export share, the proportion of the total harvest sold internationally, reflects market access and upgrading efforts, supporting Kenya's policy goal of turning increasing production into larger, steadier export volumes (IFPRI, 2020; Stats Kenya, 2025).

The share of harvests meeting Grade 1 or export-grade standards (quality grade share) and the rejection rate (portion of harvests rejected during collection, packing, or export inspection) both show compliance with sanitary, phytosanitary, and private standards. These metrics illustrate how adopting GAPs influences fruit safety, appearance, and traceability in high-value markets (Lutta *et al.,* 2024). Post-harvest losses, representing discarded or unsellable harvests, are a major challenge in Kenya's avocado industry. These outcomes help analyze GAPs adoption among Murang'a smallholders and its impact on export success and livelihoods.

1.1.3 Context of the study

This study examines Murang'a County as a case study, Kenya's leading avocado producer and a key site to understand the gap between production growth and export success. The county's avocado sector is backed by cooperatives, packhouses, and aggregation centres, notably the Murang'a Avocado Farmers Cooperative Union, linking smallholders to local and export markets in areas like Kiharu, Kandara, Kigumo, and Kangema. This infrastructure makes Murang'a one of the few counties with foundational elements for GAPs compliance and export readiness, such as cooperative bargaining, exporter links, and certification experience. Despite this support, GAPs adoption among smallholder farmers remains inconsistent, and much output does not meet export standards. Murang'a offers insights: if strong institution support, training, and contract farming don't ensure GAPs adoption despite existing infrastructure, it reveals barriers this study seeks to explore across all stages of avocado production from pre-harvest to post-harvest.

1.2 Statement of the research problem

Kenya's avocado industry operates in a growing global market with increasing demand for export-quality Hass and Fuerte avocados. However, the country has not yet translated its production increases into a corresponding share of exports. Although Kenya yields over 500,000 metric tons each year, only a small, often unstable portion, typically below 20%, is exported (USDA, 2025b). This indicates underperformance relative to its production capacity and comparative exporters (Lutta *et al.,* 2024; Stats Kenya, 2025). The persistent gap is partly due to Kenyan fruit often failing to meet strict sanitary, phytosanitary, and private standards in high-value markets, where Good Agricultural Practices (GAPs) ensure food safety, traceability, and quality (Lutta *et al.,* 2024).

Though GAPs are promoted to help smallholders improve quality and access export markets, evidence in Kenya is limited to clearly establishing a causal link between contract farming, farm size, GAPs training, and GAPs adoption. In this study, GAPs adoption was classified into farming, preharvest, and postharvest GAPs. Most studies regard standards compliance as a normative objective rather than empirically testing whether relevant issues regarding contract farming, land size and access to GAPs training have an influence on GAPs adoption (Amare *et al.,* 2019; Njuguna *et al.,* 2022). Moreover, this study attempts to disaggregate GAPs adoption by farming stage and provides data on its drivers. Despite increased training on GAPs and certification through donor and policy programs, adoption remains limited, fragmented, and uneven across counties. This suggests that the factors affecting adoption and the conditions for GAPs to be effective are not well understood (International Trade Centre, 2017; PEP, 2018).

Methodologically, the research on Kenyan avocados consists of descriptive value-chain diagnostics and lacks comprehensive empirical analysis of issues like marketing channels, training dynamics, and contract farming (Tallontire *et al.,* 2014). Moreover, it does not disaggregate adoption at various stages; thus, this study addressed this gap by modelling GAPs uptake as an adoption decision at different farming stages (Kollenda *et al.,* 2024; B. Muriithi

& Kabubo-Mariara, 2022; Njuguna *et al.,* 2022). As a result, policymakers and exporters lack solid empirical guidance on which farm-level and institutional factors most affect GAPs adoption or whether scaling compliance can boost export share. This study addresses these interconnected conceptual, contextual, and methodological gaps by (i) describing the avocado farmers in Muranga County, Kenya, and (ii) evaluating how farm size, contract farming, and access to training influence GAPs adoption among smallholder avocado farmers. The goal is to provide evidence that can guide targeted interventions to reduce Kenya's export-share gap and increase smallholder incomes.

1.3 General objective

The purpose of this study was to analyze the factors influencing the adoption of Good Agricultural Practices (GAPs) among small-scale avocado farmers in Murang'a County, Kenya.

1.3.1 Specific objectives

The study was guided by the following objectives:

i. To characterize smallholder avocado farmers in Murang'a County and assess their compliance with pre-harvest, harvest, and post-harvest GAPs and SPS standards.
ii. To analyze how farm size, measured in acres of avocado cultivation, affects the likelihood of smallholder farmers adopting pre-harvest, harvest, and post-harvest GAPs.
iii. To assess how training on GAPs in the last 12 months influences the adoption of pre-harvest, harvest, and post-harvest GAPs.
iv. To assess the influence of participating in contract farming with exporters (measured as having a formal contract) on adopting pre-harvest, harvest, and post-harvest GAPs.

1.4 Research questions

The study was guided by the following research questions:

i. What are the socio-demographic, farm-level, and economic characteristics of smallholder avocado farmers in Murang'a County, and what is their current level of compliance with pre-harvest, harvest, and post-harvest GAPs and SPS standards?
ii. What is the influence of farm size (acres under avocado) on the adoption of pre-harvest, harvest, and post-harvest GAPs?
iii. What is the effect of participation in GAPs training on the adoption of pre-harvest, harvest, and post-harvest GAPs?

iv. What is the influence of participation in contract farming with exporter companies on the adoption of pre-harvest, harvest, and post-harvest GAPs?

1.5 Scope of the study

This research focused on smallholder avocado farmers in Murang'a County, Kenya. Smallholders were defined as households that (i) own or manage at least 10 avocado trees, (ii) sold avocados during the 2024/2025 season, and (iii) earn some income from avocado farming. The study specifically targeted the three main avocado-producing sub-counties of Murang'a, Kiharu, Kandara, and Kigumo, where commercial farming is most prominent, and export connections are strongest. Respondents were selected using a multi-stage sampling process. Initially, three sub-counties were purposefully chosen based on their contribution to county avocado production and the existence of active exporter collection centres. In each sub-county, wards and villages were randomly picked with probability proportional to size. Lastly, individual farmer households were randomly selected from updated sampling frames provided by the County Department of Agriculture, avocado cooperatives, and exporter out-grower lists.

The unit of analysis was the avocado farming household, specifically the primary decision-maker responsible for orchard management and marketing decisions. The study employed a cross-sectional research design and utilized a structured questionnaire administered digitally via KoboToolbox. Data collection occurred between January and March 2025. The scope was confined to investigating the influence of farm size (acres under avocado cultivation), participation in GAPs training, and involvement in contract farming on the adoption of Good Agricultural Practices, disaggregated into pre-harvest, harvest, and post-harvest stages. While the study gathered information on production outcomes, including yield, post-harvest losses, export share, and Grade 1 produce, it did not encompass a comprehensive value chain analysis nor extend to other avocado-producing counties. Consequently, the findings are specific to smallholder avocado systems in Murang'a County and should be generalized with caution to other regions or crops.

1.6 Significance of the study

This study bears considerable importance for agricultural policy formulation in Kenya. By presenting empirical evidence concerning the relative influence of farm size, training, and contract farming on the adoption of Good Agricultural Practices (GAPs) across pre-harvest, harvest, and post-harvest phases, the findings provide valuable insights for policymakers aiming to address the persistent disparity between avocado production and export efficiency.

The results contest the conventional presumption that larger farms are inherently more capable of complying with GAPs standards and instead emphasize the significant role of institutional arrangements, such as contract farming. This evidence can inform the revision the study aligns with national strategies like the Agricultural Sector Transformation and Growth Strategy (ASTGS) and local avocado development plans. It emphasizes expanding contract farming, providing targeted subsidies for group certification, and shifting public extension services toward post-harvest practices. This research supports Kenya’s wider objectives of improving SPS compliance, boosting export earnings, and enabling smallholder farmers' inclusive access to high-value markets through initiatives such as the African Continental Free Trade Area (AfCFTA).

It also provides practical guidance for key stakeholders in the value chain, including exporters, packhouses, cooperatives, extension services, and smallholder farmers. The findings indicate that contract farming and targeted training at different stages are more effective in promoting GAPs adoption than farm size alone. Exporters and cooperatives can leverage this information to develop improved contract packages that incorporate post-harvest training, supervision, and incentives for record-keeping. Farmers and farmer groups will better understand which practices are most effective in increasing export share and achieving Grade 1 quality. Development partners and county officials can address gaps, particularly in post-harvest handling and documentation, by investing in shared infrastructure such as collection centers and affordable storage, as well as creating capacity-building programs that address the specific compliance challenges faced by smallholders in Murang’a County.

This study enhances the literature on agricultural technology and standards adoption in multiple ways. First, it integrates the Random Utility Theory (RUT) and Diffusion of Innovations (DoI) to provide a more comprehensive understanding of adoption decisions. Second, by applying a Multivariate Probit model to disaggregated stages of GAPs adoption, it reveals the interconnectedness of decisions along the value chain and identifies stage-specific drivers, challenging the common assumption of uniform effects in standards compliance. Third, the unexpected finding that smaller farms demonstrated higher pre-harvest GAPs adoption under certain institutional conditions adds depth to ongoing debates about farm size and the influence of institutional support in smallholder upgrading within global value chains. These insights offer a detailed framework for future research on bundled innovations and private standards in high-value horticulture in developing countries.

1.7 Chapter summary

This chapter offers a comprehensive background of the study within the global, African, and Kenyan contexts concerning avocado and GAPs. It clearly describes the main study outcome, the independent variable (GAPs adoption), and how it is measured. The section states the research problem, the overall objective, specific aims, and research questions. Additionally, the chapter discusses the significance and scope of the study.

1.8 Organization of the thesis

The rest of the thesis is organized as follows: Chapter presents the literature review, offering a glimpse of the theoretical and empirical framework. Chapter three presents the research methodology, discussing the research design and approaches to data analysis. Chapter four presents the results of the study, and Chapter five presents the discussion, conclusions, and recommendations.

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CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter reviews theories related to the research, offering a solid theoretical basis for the study. It includes a thorough overview of the main economic theory and empirical research, referencing prior studies aligned with the research goals. The chapter highlights key empirical work and points out the research gaps it aims to fill. Additionally, it discusses the conceptual framework, showing how the dependent and independent variables relate within the study.

2.2 Theoretical literature review

The theoretical review aims to anchor the study in its foundational principles. This research primarily relies on Random Utility Theory (RUT), with the Diffusion of Innovation Theory (DoI) supplementing it to explain the adoption of Good Agricultural Practices (GAPs). es (GAPs).

2.2.1 Random Utility Theory (RUT)

Building on McFadden's influential 1974 work, Random Utility Theory (RUT) proposes that decision-makers, such as avocado farmers in this context, select GAPs based on perceived utility, which includes both a deterministic component and a random (stochastic) component (McFadden & Richter, 1990). RUT plays a crucial role in microeconomics, particularly for modeling decision-making under uncertainty. The utility derived from adoption can be measured and observed through factors like expected yield improvements, costs, or access to inputs (Montes de Oca Munguia *et al.,* 2021). The error term accounts for unobserved differences, including personal attitudes, risk preferences, and social influences (Lipińska, 2016). Moreover, RUT provides a structured way to analyse individual choices amid uncertainty. It states that each farmer assigns a utility value to each feasible option, such as adopting or not adopting GAPs, and selects the one with the highest perceived utility. Moreover, it can explicitly capture the heterogeneity among the sampled respondents. Part of this utility depends on observable factors such as input costs and training availability, while the rest stems from unobservable or "random" factors like personal risk tolerance, trust in extension agents, or social influences (Joao *et al.,* 2015). Adoption is probabilistic; two farmers with similar characteristics may still differ in behaviour due to unobserved variations, precisely what RUT models. In the context of avocado GAPs adoption, this framework offers an anchoring basis since yield expectations could affect adoption rates (Kassie *et al.,* 2015).

This makes RUT particularly useful for testing hypothesis effects and designing targeted interventions. Formally, utility of the farmer i derives from a choice of alternative j, such as adopting GAPs, can be expressed as (Horowitz *et al.,* 1994):

$$U_{ij} = V_{ij} + \varepsilon_{ij}$$

Where V_{ij} is the observable, systematic utility, and ε_{ij} is the unobservable, random component. The decision-maker chooses alternative j if and only $U_{ij} > U_{ik}$ if for all $k \neq j$. In the context of agricultural adoption studies, this means that a farmer will adopt a particular practice, such as pruning, pest management, or improved harvesting methods, if the perceived benefits outweigh the perceived costs compared to other available options (Feder *et al.,* 1985). One of RUT's greatest strengths lies in capturing heterogeneity in decision-making. Farmers may have similar observable conditions but diverge in behaviour due to unobserved variables like educational background, risk tolerance, or social network position (Aryal *et al.,* 2018).

RUT-based discrete choice models, such as logit and probit, enable researchers to quantify probabilistic adoption likelihood, rather than assuming deterministic behaviour, thereby reflecting real-world variability with greater accuracy (Greene, 2005; Greene, 2003). For example, two avocado farmers with identical land size and access to training may adopt differently due to differences in perception or unmeasured cultural beliefs. Previous research on adoption utilizes Random Utility Theory (RUT) through discrete choice models. These models explain farmers' acceptance of innovations by linking their choices to perceived benefits from specific practice attributes.

For instance, studies on greenhouse tomato technologies and variety selection in Israel reveal how regional, local, and individual farmer factors influence utility and adoption decisions (Shefer *et al.,* 2004). Similar approaches in Burkina Faso show that perceptions and access to training significantly affect the likelihood of adopting conservation practices (Emvalomatis *et al.,* 2019). RUT's key strength is its ability to account for behavioural diversity: factors like experience, education, gender, headship, and risk attitudes systematically influence utility calculations and adoption chances (Joao *et al.,* 2015; Serraino & Uryasev, 2013). Because utility includes an unobserved random component, RUT supports probabilistic estimators such as logit and probit.

This enables policy simulations, such as evaluating how subsidies, demonstration-based training, or better market access could improve the perceived utility of GAPs and increase adoption (Cascetta, 2009; Diagne *et al.,* 2022). It also models adoption amid information uncertainty, where incomplete knowledge is represented by the stochastic term and updated through learning from extension services or peers over time (Foster and Rosenzweig, 1995; C. Rosenzweig *et al.,* 2014; Rosenzweig and Binswanger, 1993).

Importantly, RUT accommodates both economic and non-economic motivations, including yield gains, income, phytosanitary compliance, environmental stewardship, and social recognition, within a unified decision framework (Aguiar *et al.,* 2023; Delgado *et al.,* 2017; Vignola *et al.,* 2010). For example, in avocado farming, RUT suggests that farmers choose specific GAPs options (such as IPM, pruning, mulching, and safe pesticide use) when the perceived net utility is highest. Additionally, mixed-logit models capture the diversity of preferences among smallholders (F. D. J. Davis, 1985; Feder *et al.,* 1985; Feyisa, 2020; Førsund *et al.,* 1980; Kariuki, 2025; Regassa *et al.,* 2023).

In this study, RUT supports Objectives ii, iii, and iv by assuming Murang'a avocado farmers will adopt GAPs when the benefits, higher export prices, reduced post-harvest losses, better fruit quality, and sustained market access, outweigh the costs and risks of non-adoption. Observable variables such as farm size (acres under avocado cultivation), receipt of GAPs training in the last 12 months, and participation in formal contract farming with exporters are expected to positively shift the deterministic component of utility, thereby increasing the probability of adoption across pre-harvest, harvest, and post-harvest stages. The stochastic component captures unobserved heterogeneity in risk preferences, managerial ability, and local conditions. This theory directly underpins the Multivariate Probit model used to estimate the influence of these variables on stage-specific adoption probabilities (Objectives ii–iv). For Objective i, RUT also helps explain variations in observed compliance levels by linking farmer and farm characteristics to utility calculations. However, RUT has limitations in the Murang'a smallholder context. Its assumption of individualistic utility maximisation may downplay collective decision-making and power asymmetries in exporter contracts (Joao *et al.,* 2015). It also assumes access to complete information, unlike the information gaps many farmers experience. These limitations are addressed by integrating with DoI Theory.

2.2.2 Diffusion of Innovations (DoI) Theory

Everett M. Rogers developed the Diffusion of Innovations (DoI) Theory in 1962, creating one of the most influential frameworks for explaining how, why, and at what pace innovative ideas and technologies spread within a social system (Rogers, 1975). He defined diffusion as "the process by which an innovation is communicated through certain channels over time among members of a social system" (Sahin, 2006). This theory provides a conceptual basis for understanding the spread of agricultural technologies and management practices, including Good Agricultural Practices (GAPs) in avocado farming. Frameworks such as the DoI emphasise the social, communicative, and psychological processes underlying adoption, making it particularly useful in settings where interpersonal influence, community norms, and information flows play a critical role in farmers' decision-making (Sahin, 2006).

At its core, DoI identifies four key elements in the diffusion process: (1) the innovation itself, (2) the communication channels through which information about the innovation flows, (3) time, which captures both the innovation-decision process and the adoption curve, and (4) the social system within which diffusion occurs (Rogers, 1975). In the context of avocado farming, GAPs such as proper pruning, disease control, harvesting techniques, and post-harvest handling represent the innovation (Simon *et al.,* 2023). Extension services, farmer field schools, mobile agricultural apps, and peer-to-peer learning serve as the communication channels. Time reflects how quickly farmers move from awareness to adoption, while the social system includes farmer cooperatives, local market networks, and village-level community structures (Kariuki, 2025).

A fundamental contribution of DoI is the classification of adopters into categories, innovators, early adopters, early majority, late majority, and laggards, based on their propensity to adopt an innovation (Baig *et al.,* 2005). Innovators are venturesome individuals willing to take risks, often with higher access to resources and external information sources (García-Avilés, 2020). In avocado GAPs adoption, these might be progressive farmers experimenting with organic certification or integrated pest management before others in the community. Early adopters are respected opinion leaders who influence others' decisions; their success with GAPs adoption can accelerate diffusion. The early majority adopt after seeing benefits among peers, while the late majority are sceptical and adopt due to social pressure or economic necessity. Laggards are the most resistant, constrained by limited resources, low risk tolerance, or attachment to tradition (Baig *et al.,* 2005).

Understanding these adopter categories helps extension officers design tailored interventions, for example, focusing pilot programs on innovators and early adopters, then leveraging their experience to influence the rest across gender aspects (Muriithi and Kabubo-Mariara, 2022). Another key insight from DoI is the innovation-decision process, which unfolds in five stages: (1) knowledge, awareness of GAPs and understanding their functions, (2) persuasion, forming attitudes towards GAPs, influenced by perceived advantages, compatibility with existing practices, and complexity. The third stage is (3) decision, choosing whether to adopt or reject, (4) implementation, putting GAPs into practice, and (5) confirmation, seeking reinforcement for the decision or reversing it if dissonance occurs (Turner, 2007; Turner, 1996).

For avocado farmers, the knowledge stage may come from training workshops or agricultural extension visits; persuasion could be shaped by observing reduced post-harvest losses among GAPs adopters; decision-making may hinge on cost-benefit analysis; implementation involves altering day-to-day farming routines; and confirmation occurs as farmers observe improvements in yield quality and market prices (Scott *et al.,* 2008), which also ensures that farmers are not disadopters after uptake of a technology (Wangithi *et al.,* 2021). DoI also identifies five perceived attributes of innovations that strongly influence adoption rates: relative advantage, compatibility, complexity, trialability, and observability (Roger, 1995). Relative advantage refers to the degree to which GAPs adoption is perceived as better than existing practices; for instance, farmers may adopt improved pruning methods if they visibly increase yields or market access.

Compatibility measures how consistent GAPs are with cultural beliefs, existing infrastructure, and farming systems; GAPs requiring expensive irrigation infrastructure may be less compatible for rain-fed farmers. Complexity refers to the difficulty in understanding and implementing GAPs; simple practices like correct spacing of avocado trees may diffuse faster than more technical practices like integrated pest management. Trialability, the ability to test GAPs on a small scale, can lower dis-adoption risks; farmers may adopt organic composting methods on a small plot before applying them farm-wide. Observability, the extent to which results are visible to others, can accelerate adoption, as seeing a neighbour's healthier, higher-yielding orchard can be a motivator (Rogers, 1975).

One of the strengths of DoI is its recognition that social networks and opinion leaders can significantly influence diffusion patterns (Ruzzante *et al.,* 2021). In Kenyan avocado farming communities, farmer cooperatives, savings and credit groups, and social networks often serve as platforms for sharing agricultural innovations (Matabi *et al.,* 2022). Opinion leaders, often early adopters, can bridge the gap between formal extension services and the broader farming community, translating technical language into practical advice and demonstrating results through their adoption. Thus, it complements quantitative adoption models by integrating the human, relational, and communicative aspects (Dearing, 2009). However, DoI is not without limitations, with critics arguing that it can be overly linear and individualistic, assuming a universal adoption sequence that may not hold in all contexts (Zondo and Ndoro, 2023). In rural agricultural settings, adoption may be heavily influenced by collective decision-making, resource constraints, market access, and external shocks such as climate variability (Frei-Landau *et al.,* 2022). Furthermore, DoI does not account for economic trade-offs or the role of policy incentives, which means it benefits from integration with economic models like RUT to capture the full range of adoption determinants (Takahashi *et al.,* 2020). Despite its limitations, DoI is valuable as it highlights how the social environment and communication pathways can accelerate or impede the spread of GAPs (Feder *et al.,* 1985).

From a policy standpoint, DoI provides actionable insights for enhancing GAPs adoption among avocado farmers in Kenya. Extension programs can be designed to target early adopters and opinion leaders, who can then influence others through demonstration plots, farmer-to-farmer exchange visits, and public recognition (Baig *et al.,* 2005). Information campaigns can be tailored to emphasise the relative advantage and compatibility of GAPs, while training sessions can be structured to reduce complexity and increase trialability (Masambuka-Kanchewa *et al.,* 2020). Visibility can be enhanced by documenting and broadcasting success stories via community radio, social media, and agricultural fairs. By systematically addressing the perceived attributes of innovations, policymakers and development partners can accelerate the diffusion curve and achieve higher adoption rates. The Diffusion of Innovations theory provides a socially grounded perspective on how avocado farmers in Kenya adopt GAPs. It highlights the influence of communication, peer interactions, and social networks, as well as the characteristics of the innovation itself. When researchers integrate this theory with formal econometric approaches such as the Random Utility Theory, they gain a more comprehensive understanding of adoption dynamics, addressing both the social and economic dimensions of farmers' decisions in designing and evaluating agricultural interventions.

DoI firmly endorses all four objectives. For Objective i, it explains differences in GAPs compliance by exploring how farmers view GAPs as an innovation and how information circulates in communities. Regarding Objectives ii, iii, and iv, DoI suggests that adoption increases when farmers see clear benefits (such as through contract farming), perceive better compatibility, perceive less complexity (with training in the past 12 months), and observe peers' successful practices. In Murang'a, where cooperatives and exporter linkages are crucial, DoI highlights how training and contract farming serve as diffusion channels, speeding up the adoption of pre-harvest, harvest, and post-harvest GAPs. Despite its strengths, DoI has important limitations in this context. Its linear and individualistic orientation inadequately accounts for structural barriers such as high compliance costs, credit constraints, and top-down contractual enforcement, which are typical of Murang'a's avocado value chain (Zondo & Ndoro, 2023). The framework also under-emphasises economic trade-offs, creating inconsistencies when explaining why post-harvest practices lag despite strong pre-harvest adoption. These gaps are mitigated by integrating DoI with RUT.

2.2.4 Choice of theories of the study

The selection of Random Utility Theory (RUT) and Diffusion of Innovations (DoI) Theory reflects the dual nature of GAPs adoption in avocado farming, which involves both economic decision-making and social diffusion. Even when farmers are aware of recommended practices, they intentionally choose among combinations of practices based on anticipated net benefits. RUT, grounded in the random-utility framework established in discrete-choice theory , offers the economic foundation for the adoption models used in this study. The theory assumes that farmers select the option that maximises their perceived utility, while allowing an unobserved stochastic component that captures incomplete information and preference diversity. This is particularly relevant in Murang'a County, where avocado farmers face heterogeneous farm sizes (acres under avocado cultivation), risk attitudes, market channels, and resource constraints. RUT-based models, like the Multivariate Probit estimator used here, measure how factors such as farm size, recent GAPs training within the last year, and involvement in contract farming with exporters influence adoption probabilities during pre-harvest, harvest, and post-harvest stages). This directly supports Objectives ii, iii, and iv of the study. Additionally, GAPs is not a single input but a complex, multi-component standard that gradually disseminates through farmer networks, extension systems, and export-chain institutions over time (Manski, 1977, 2001). Therefore, DoI Theory (Rogers, 1975) is crucial for explaining how and why GAPs spreads across communities.

The theory suggests that adoption rates depend on perceived attributes of the innovation such as relative advantage, compatibility, complexity, trialability, and observability along with communication channels and the social system. These constructs map directly onto GAPs adoption in avocado production: farmers' perceptions of export price premiums and market access (relative advantage), fit with current orchard routines (compatibility), audit and record-keeping demands (complexity), opportunities to gain experience through training and demonstrations (trialability), and visible success of certified peers (observability) shape diffusion intensity. DoI is widely used in agricultural standard-adoption research for exactly this type of bundled practice spreading through social and institutional networks (Oturakci & Yuregir, 2018; Shang *et al.,* 2021). This framework supports all four objectives by helping explain varying compliance levels (Objective i) and the mechanisms through which training and contract farming facilitate diffusion (Objectives iii and iv).

Taken together, RUT and DoI are complementary rather than redundant. RUT provides the econometric logic for modelling farmers' discrete adoption choices under heterogeneity and uncertainty, while DoI explains the broader social and institutional diffusion processes of GAPs as a standards package. This integrated theoretical grounding responds to critiques that purely economic models under-explain adoption in smallholder settings. It strengthens the study's ability to link economic drivers (farm size and contract farming), information and learning processes (training), and diffusion pathways to observed GAPs adoption and export outcomes in the Murang'a avocado context (Tinh *et al.,* 2021).

2.3 Empirical literature review

This section critically reviews existing empirical studies on the adoption of Good Agricultural Practices (GAPs), examining the factors that influence their uptake and the resulting effects on productivity, quality, and market access. It examines past studies identifying patterns, strengths, and limitations, while highlighting how these insights inform the present research. The review not only synthesises findings across diverse contexts and value chains but also evaluates the methodologies, variables, and analytical frameworks employed. It brings to light key knowledge gaps, contextual differences, and empirical shortcomings that remain unaddressed. It identifies synergies between prior work and the objectives of this study, ensuring that the current research builds on a good foundation while contributing new evidence and perspectives to GAPs adoption.

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2.3.1 Adoption of Good Agricultural Practices (GAPs) across horticultural value chains

This section reviews empirical studies on GAPs adoption in horticultural value chains, organised thematically around the three stages of GAPs adoption that correspond to the study's objectives: pre-harvest, harvest, and post-harvest practices. For each stage, the review discusses evidence on the influence of farm size, training, and contract farming where available, identifies indicators used, and concludes with a clear statement of empirical gaps. A final subsection critically examines methodological approaches and explains how this study improves upon prior work despite cross-sectional data limitations.

2.3.1.1 Adoption of pre-harvest GAPs

Pre-harvest GAPs include soil management, fertilizer application, irrigation, pest and disease control (such as integrated pest management), the use of approved pesticides, sanitation, and record-keeping. Empirical research consistently indicates that the adoption of these practices is influenced by factors such as farmer training, access to extension services, and farm size, although the evidence varies by crop and context Chelang'a *et al.* (2023) assessed compliance standards among smallholder French bean producers in Murang'a County, Kenya, using a random sample of 215 households and applying multivariate probit and endogenous switching models. They observed that contract participation, buyer support, including training on pre-harvest practices, and membership in producer groups significantly increased the likelihood of complying with pre-harvest standards such as pesticide management and field sanitation.

The study aggregated 'compliance' into a single score without specifically isolating pre-harvest practices. Gichuki *et al.* (2020) examined how household wealth and access to finance influence the adoption of GlobalG.A.P. among Kenyan smallholders. They discovered that higher asset levels and greater credit access significantly increase the chances of meeting pre-harvest requirements. However, their cross-sectional probit models did not consider potential endogeneity. Wangithi *et al.* (2022) provided experimental evidence on integrated pest and pollinator management (IPPM) in avocado farms in Kenya and Tanzania, demonstrating that training via farmer field schools markedly improved pre-harvest pest control and reduced fruit damage. Although their experimental approach offers high internal validity, it might not fully reflect the adoption behaviors influenced by market constraints. Empirical gaps concerning pre-harvest adoption include limited avocado-specific data for Murang'a County, particularly regarding how training and contracts influence practices such as IPM adoption, pesticide dosage compliance, and sanitation record-keeping. There is also weak causal inference due to dependence on cross-sectional data and the lack of consideration for self-selection into training or contracts. Furthermore, the study does not distinguish between pre-harvest, harvest, and post-harvest adoption stages. To address these issues, this research treats pre-harvest adoption as a separate binary outcome, analyzing data from Murang'a avocado farmers. It assesses the influence of training and contracts on pre-harvest GAPs using a multivariate probit model that accounts for correlated decisions, while explicitly recognizing the limitations of cross-sectional data and controlling for observable confounders.

2.3.1.2 Adoption of harvest GAPs

Harvest GAPs involve using clean tools, hand-picking avocados at the right maturity, preventing fruit drop, and using poles with baskets to avoid damage. While pre-harvest and post-harvest practices have been more extensively studied, harvest GAPs have received less empirical attention, partly because they are often seen as less complex or because harvest methods are rarely documented separately. Muita *et al.* (2025) studied factors driving post-harvest losses in Murang'a County, highlighting that poor harvest timing and incorrect picking methods significantly damage fruit and increase losses. Their research did not treat harvest GAPs adoption as a separate outcome but instead incorporated harvest practices into a broader framework of loss factors.

Across other horticultural value chains, Cromwell *et al.* (2025) pinpointed crew skills, supervision, and harvest logistics as key factors affecting rejection rates at packhouses, showing that harvest practices directly influence product quality downstream. However, specific evidence for avocados remains scarce. Amare *et al.* (2019b), in their study of participation in avocado exports, found that farmers selling to exporters were more likely to follow buyer-specified harvest protocols, although they did not measure harvest practice adoption directly. Gaps in empirical research include a lack of studies that treat harvest GAPs as a distinct outcome. There is also limited evidence on how training or contract farming influences harvest-stage compliance in avocados. Additionally, it is unclear whether farm size influences harvest practices differently than pre- or post-harvest routines. This study intends to address these gaps by modeling harvest GAPs adoption as a binary variable (e.g., using clean tools, hand-picking, pole-with-basket methods), analyzing the separate effects of farm size, training, and contracts with a multivariate probit model, and exploring the correlations between harvest and post-harvest practices to identify potential complementarities.

2.3.1.3 Adoption of post-harvest GAPs

Post-harvest GAPs encompass proper produce storage, washing, handling with crates, sorting, waste disposal, adherence to pesticide withdrawal periods, and traceability/record-keeping. This stage is known as the critical point where produce quality and safety are most vulnerable, particularly in tropical fruit export chains with inadequate cold-chain infrastructure (Sheahan & Barrett, 2017b). Muita *et al.* (2025) identified key factors such as poor storage, inadequate packaging, limited packhouse access, and lack of pre-cooling as major causes of high post-harvest losses among avocado farmers in Murang'a County. Their fractional-response regression revealed that farmers who employed sorting, used crates, and practiced proper waste disposal experienced significantly lower loss rates. However, the study did not connect specific post-harvest practices to market outcomes such as packhouse acceptance or pricing. Lutta *et al.* (2024) assessed technologies to reduce post-harvest losses in East Africa, finding that improved packaging and cold storage can enhance grades and decrease losses, but they concentrated on capital-intensive solutions rather than affordable practices suitable for smallholders. In Ghana's mango sector, (Akrong *et al.,* 2021, 2022) observed that GlobalG.A.P. certification, which includes post-harvest handling standards, improved export access, though the study did not specify which post-harvest GAPs were most vital for acceptance.

Cromwell *et al.* (2025) emphasized that post-harvest handling directly influences packhouse rejection rates, yet quantitative data on how individual practices (like crate use, pre-cooling, and traceability) affects export share or grade quality are missing for Kenyan avocados. Post-harvest adoption gaps include limited evidence connecting specific practices, such as sorting, crate use, pre-cooling, traceability, and withdrawal period compliance, to measurable market outcomes like export share, Grade 1 percentage, or rejection rates at the packhouse. There is also a lack of avocado-specific analysis on how institutional factors including contracts, group membership, and extension services influences post-harvest practices adoption. Furthermore, the role of training in enhancing post-harvest handling receives inadequate attention, as most training programs focus on pre-harvest production. This study addresses these issues by assessing post-harvest adoption as a binary outcome across multiple practices, examining how contract farming and training influence post-harvest GAPs, and comparing export shares and Grade 1 proportions between high and low GAPs adopters through t-tests. Additionally, it highlights the low training rates on post-harvest management (under 6%), signaling a significant policy gap.

2.3.2 Approaches used in the analysis of adoption

In empirical research on adoption, scholars use various econometric frameworks, each with their own advantages and limitations. The simple univariate binary probit or logit models are easy to apply for a single adoption choice but do not consider potential interdependence between multiple practices, which can lead to biased or inefficient estimates when adoption involves multiple dimensions (Chen & Tsurumi, 2010). Count models, such as Poisson or negative binomial regressions, quantify adoption intensity by modeling the number of practices adopted, but they treat all practices as interchangeable and do not reveal potential complementarities or sequences (Coxe *et al.,* 2009). Tobit and fractional response models are suitable for censored or proportional data but still reduce multidimensional behavior to a single measure (Terza, 1985). Multinomial logit or ordered models allow for comparisons among mutually exclusive outcomes (choosing practice A over B), but they assume choices are exclusive and rely on the IIA assumption (Variyath & Brobbey, 2020). In contrast, the multivariate probit (MVP) model is tailored for analyzing multiple, correlated binary decisions about adoption. It permits the error terms across different equations to be freely correlated, effectively capturing the complementarity or substitution between practices.

MVP has been utilized in various agricultural contexts, such as climate-smart practices (Jara-Rojas *et al.,* 2013), improved rice technologies in Ethiopia (Yirga *et al.,* 2015), and soil-carbon-enhancing practices in Kenya (Kanyenji *et al.,* 2020) and adoption of integrated disease management practices for maize diseases (Kimani *et al.,* 2026) . Since this study examines the simultaneous and progressive adoption of three GAP categories, pre-harvest, harvest, and post-harvest, that are likely interdependent, the MVP model is most suitable. It allows for estimating the individual adoption probabilities for each stage, reveals inter-practice correlations (ρ_{12}, ρ_{23}, ρ_{13}), and prevents biases that could occur if separate univariate probits were used.

A key methodological concern across the literature is the heavy dependence on cross-sectional data. Most adoption studies, including many reviewed above, cannot establish causality due to potential endogeneity (unobserved farmer ability influences both training participation and GAP adoption) and selection bias (exporters contracting with already- compliant farmers). Some studies have employed more sophisticated methods, such as endogenous switching regression (Amare *et al.,* 2019b; Chelang'a *et al.,* 2023), instrumental variables (though rarely used due to difficulties in finding credible instruments), or propensity score matching (Mwambi *et al.,* 2016).

This study does not utilize these advanced causal techniques because of the lack of valid instruments that affect training or contract participation without directly influencing GAP adoption, the cross- sectional data structure, and its focus on modeling joint adoption decisions suitable for MVP rather than isolating causal effects of a specific treatment. Consequently, the study does not address the causal limitations inherent in cross- sectional research. Instead, it adopts a transparent and modest approach: employing MVP to account for correlated unobservable across adoption stages (which reduces omitted variable bias compared to single-equation probits); controlling for a comprehensive set of variables (household demographics, farm characteristics, institutional factors, and ward fixed effects); using cluster- robust standard errors to handle within- ward correlation; testing explicitly for the endogeneity of training and contract variables via a control- function approach; and interpreting all estimates as conditional associations rather than causal effects. The study also emphasizes the need for future research using panel data or quasi- experimental designs, as no Kenyan avocado study has yet employed a randomized controlled trial, natural experiment, or panel data with fixed effects to convincingly establish the causal effect of training or contracts on GAP adoption. This remains a vital avenue for future investigation, and the current study does not address this gap.

2.4 Factors influencing the adoption of GLOBAL GAPs across agricultural value chains

Empirical evidence on standards and GAP adoption is broadly consistent that adopters differ systematically from non-adopters, but the strength of causal claims varies with methodology. Cross-sectional export–non-export comparisons show sizable income and performance gaps, yet these designs struggle with endogenous selection because more capable or better-resourced farmers self-select into export channels, making estimates upward-biased without correction (Amare *et al.,* 2019). Studies that model adoption with institutional variables typically find positive effects of extension contact and producer-group membership, but most Kenyan papers rely on probit/logit using single-equation cross-sections, so they capture associations rather than mechanisms; few test for unobserved heterogeneity in information quality or group effectiveness (Chelang'a *et al.,* 2021, 2023; Nthambi *et al.,* 2013). Behavioural studies add perceived benefits, costs, and risk preferences, improving explanatory power by showing that adoption is shaped by subjective expected returns and risk attitudes, not just liquidity; however, many of these works measure perceptions with simple Likert items and do not adequately address reverse causality (adoption itself may change perceived risk/benefit), which weakens inference (Kibet *et al.,* 2018; Lippe and Grote, 2017).

Cost-focused analyses highlight the fixed-cost and scale barriers to compliance and correctly motivate group certification and buyer financing as solutions, but they often treat costs as uniform across farmers and regions, underplaying how agro-ecological conditions or buyer enforcement intensity alter cost–benefit ratios (GLOBAL G.A.P, 2022). Asset-endowment findings are consistent across contexts; wealth and finance access predict adoption in Kenya, Thailand, and Peru. However, most studies treat wealth as a static proxy and do not clarify if wealth boosts adoption by easing liquidity, improving risk capacity, or enabling market ties. (Gichuki *et al.,* 2020; Lemeilleur, 2013). Quasi-experimental and switching-regression studies with contracting and exporter support better identify effects than pure cross-sections by partially correcting for selection. However, they often focus on a single crop and standard, limiting applicability to avocado systems with different compliance bundles and buyer governance (Amare *et al.,* 2019). The reviewed literature converges on the importance of institutions, , but methodological reliance on cross-sectional self-reported data means the causal pathway from GAP compliance to export outcomes remains under-tested, the gap this avocado study addresses.

2.4.1 Influence of farm size on GAPs adoption among avocado farmers

Empirical studies on private standards consistently show that farm size (hectares under cultivation or total landholding) is positively associated with GAP/GlobalG.A.P. adoption because larger farms can spread fixed compliance costs (infrastructure, audits, record systems) over higher output volumes. Evidence from Kenyan export horticulture indicates that smallholders face disproportionately high per-unit costs, making adoption less attractive unless they scale up or certify collectively (Asfaw *et al.,* 2009; Ouma, 2008). Recent compliance-cost work in other smallholder export chains similarly finds strong scale economies: fixed investments and recurrent audit requirements create a size threshold below which certification is financially difficult (Annor *et al.,* 2024). Methodologically, however, most studies estimate farm-size effects using cross-sectional probit/logit models, which identify correlations but rarely address endogeneity (farm size may itself be influenced by prior commercialisation or exporter targeting) (Chelang'a *et al.,* 2023). Empirical gaps: (1) limited avocado-specific evidence for Kenya/Murang'a; most findings are inferred from other crops (beans, pineapple, mango). (2) causal identification of scale effects due to cross-sectional self-selection. (3) limited testing of size thresholds or interaction with collective certification and contracts.

2.4.2 Role of training on GAPs adoption among avocado farmers

Across African smallholder systems, training/extension exposure measured by number of trainings attended, frequency of extension visits, or participation in demonstrations, emerges as one of the robust predictors of adoption of complex practice bundles like GAPs. A systematic review of adoption studies shows consistent positive effects of training and access to information on uptake intensity, especially for innovations that require knowledge and repeated practice (Li *et al.,* 2024). In Kenya, GLOBALG.A.P. adoption studies in export horticulture also report that extension contact and group-based learning lower information costs and increase compliance probabilities (Chelang'a *et al.,* 2021). Methodologically, though, many papers rely on farmers' self-reported training exposure and do not adjust for placement bias: training programs are often targeted at commercially promising or well-connected farmers, which can exaggerate estimated effects. In addition, training is frequently treated as a binary variable, masking differences in training quality, duration, or content relevance to specific GAPs domains (pesticide safety vs. post-harvest hygiene). Empirical gaps: (1) little Murang'a avocado evidence separating which GAPs components respond most to training. (2) limited causal treatment of training endogeneity/targeting. (3) sparse measurement of training intensity and quality beyond "trained/not trained."

2.4.3 Influence of contracts with exporter companies on GAPs adoption

Studies of standards in African horticulture show that exporter contracts and buyer support (input credit, technical advice, payment of certification fees, guaranteed markets) raise both adoption and sustained compliance, because buyers internalize some costs and enforce practices through monitoring (Asfaw *et al.,* 2009). Kenyan evidence from GLOBALG.A.P. value chains indicates that contractual arrangements often function as the key institutional vehicle through which standards diffuse to smallholders, especially via group certification and exporter-led training (Chelang'a *et al.,* 2021). Compared to simple cross-sectional studies, work using quasi-experimental or switching-framework approaches provides stronger identification of contract effects, but even these studies often focus on a single crop or region, limiting transferability to avocado systems where governance and enforcement differ. Another methodological weakness is that contracts are usually measured as a binary "has contract" dummy, without capturing contract terms (price premiums, input packages, monitoring intensity) that determine compliance incentives. Empirical gaps: (1) few avocado-focused studies in Kenya quantify contract effects on GAPs uptake. (2) limited detail on contract heterogeneity and enforcement intensity. (3) continued risk of selection bias because exporters contract more capable or better-located farmers (Tallontire *et al.,* 2014). The literature agrees that farm size, training, and exporter contracts matter for standards adoption, but the evidence base for Kenyan avocados, especially Murang'a, is thin, and existing methods rely heavily on cross-sectional associations, coarse indicators, and limited treatment of endogeneity. This study addresses these empirical gaps by (i) generating Murang'a-specific data on multiple GAPs domains, (ii) measuring farm size, training intensity, and contract linkage with clearer indicators, and (iii) modelling adoption decisions in ways that allow heterogeneity and joint adoption to be evaluated more rigorously.

2.5 Summary of literature gaps

In summary, the theoretical and empirical literature reviewed in this chapter establishes that GAPs adoption is shaped by interacting socio-economic, institutional, and behavioural factors, yet four interrelated gaps stand out as directly relevant to this study. The first is a stage-specific gap: most studies, including those situated in Kenyan horticulture, treat GAPs compliance as a single aggregate score or focus narrowly on one production stage, so the determinants and consequences of pre-harvest, harvest, and post-harvest adoption are rarely examined as distinct, potentially correlated decisions. The second is a determinant-specific gap concerning farm size, training, and exporter contracts, the three variables central to this study, for which avocado-specific Kenyan evidence is scarce and existing measures are often coarse binary indicators that mask variation in scale, training intensity, and contract terms. The third is a methodological gap rooted in an almost universal reliance on cross-sectional data, which leaves the causal pathways from these determinants to GAPs adoption, and from adoption to market outcomes, largely untested. The fourth is a contextual gap: much of the evidence cited above is drawn from other crops, such as French beans, mangoes, and pineapples, or from other countries, so avocado-specific findings for Murang'a County remain limited despite the county's standing as Kenya's leading avocado-producing region. Table 2.1 illustrates these gaps with reference to a selection of the key studies reviewed, summarising their objectives and findings, the specific gap each leaves open, and how the present study responds.

Table 2.1: A summary of Literature Gaps

Title / Research	Objective	Findings	Research Gap Identified	How to Address the Research Gap
Chelang'a *et al.* (2023) – French-bean standards compliance	Examine determinants of coordination and compliance with buyer standards	Contract participation, buyer support, group membership, assets, market proximity, extension access increase compliance	Adoption aggregated into a single score; no analysis of practice-level adoption	Disaggregate GAPs adoption into pre-, harvest, and post-harvest practices and model them jointly
Gichuki *et al.* (2020) – Wealth and GLOBALG.A.P. adoption	Assess the effect of household wealth and finance on adoption/compliance	Higher asset index and credit access increase adoption and compliance intensity	No analysis of interaction between socio-economic and institutional factors at practice level	Include interaction terms in a multivariate probit to examine combined effects on adoption
Amare *et al.* (2019) – Avocado export participation	Determine impacts/determinants of export market participation	Exporters earn higher prices/incomes; selection driven by farm size, training, tree stock, group presence	No link between specific GAPs and productivity/market outcomes	Measure practice-level adoption and link to yield, quality, and market prices using causal estimators
Wangithi *et al.* (2022) – IPPM trial impacts	Estimate productivity/quality benefits and welfare gains from IPPM	High BCR; reduced pest damage; improved quality	Trial-based; lacks real-world adoption determinants	Use observational data to estimate adoption drivers and effects of IPPM components in real contexts
Muita *et al.* (2025) – Post-harvest handling and losses	Identify determinants of post-harvest losses in avocado	Poor harvest timing, inadequate packaging, lack of packhouse/pre-cooling increase losses	Limited to one county; no link between practice adoption and market access/prices	Sample across AEZs; link post-harvest practice adoption to packhouse acceptance and price incentives
Amare *et al.* (2019) – Avocado export markets	Assess impact of export participation on yields, prices, incomes	Exporters achieve higher yields and prices; advantages partly due to selection effects	Does not decompose which GAPs practices drive yield/price gains	Measure practice-level adoption (pre-, harvest, post-harvest) and estimate causal effects using selection-correcting models
Chelang'a *et al.* (2021) – Vertical coordination and standards	Analyze role of contracts and compliance in productivity	Contracts and compliance linked to larger export variety areas, higher marketed volumes	Aggregates compliance; no direct yield effect by GAP practice	Estimate direct contributions of specific GAPs practices to yield and output

Fiankor *et al.* (2020) – GLOBALG.A.P. and exports	Link certification prevalence to export volumes	Certification associated with higher export volumes and entry to high-value markets	Macro-level; lacks micro-level causal links between GAPs adoption and farm outcomes	Provide micro-level estimates linking GAPs adoption to productivity and market access
Kassem *et al.* (2021) – Private standards in citrus	Identify drivers of compliance and quality improvements	Buyer support, group membership increase compliance; improved handling where buyers invest	No causal estimates linking specific post-harvest practices to market outcomes	Link post-harvest practice adoption to packhouse rejection rates and price premiums
GLOBALG.A.P. / TAHA Tanzania (2020) – Capacity building	Evaluate the impact of training and demonstrations	Improved awareness and basic compliance; persistent capacity/cost constraints	Descriptive; no counterfactual estimation of practice effects	Apply rigorous causal methods to estimate practice–market outcome links
Cromwell *et al.* (2025) – Export pressures and post-harvest	Examine the role of harvest/handling in rejections	Crew skills, supervision, and logistics affect rejection rates	No quantitative yield/price estimates by practice	Quantify cost-effectiveness and price impacts of specific post-harvest practices

Source: Literature review (2025)

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Regarding harvest GAPs, studies rarely consider harvest practices as a separate adoption outcome, and there' s no avocado- specific data on factors affecting harvest compliance or how farm size, training, and contracts influence this stage. For post- harvest GAPs, gaps involve limited links between practices like sorting, crate use, pre- cooling, and traceability and measurable market outcomes such as export share, Grade 1 percentage, or rejection rates. Additionally, there' s insufficient analysis of how institutional factors like contracts and extension influence post- harvest adoption, and a notable lack of training on post- harvest management. Methodologically, the literature mainly relies on cross- sectional data without addressing endogeneity or selection bias. Although advanced techniques like ESR and IV are mentioned, they are rarely applied in avocado research. The current study aims to fill stage-specific gaps by disaggregating GAPs adoption into three outcomes based on primary data from Murang'a County, evaluating the effects of farm size, training, and contracts using a multivariate probit model, and linking post-harvest practices to export performance through mean comparisons. However, the issue of causal inference remains partially unaddressed and is acknowledged as a limitation, with recommendations for future studies to use panel or quasi-experimental designs. Additionally, much of the existing research is geographically limited, focusing on single locations or narrow contexts, which hampers generalizability across different agroecological zones and markets. Many studies also overlook the potential for adopting multiple GAPs simultaneously or in a complementary manner, often analyzing each practice in isolation or using univariate models. Addressing these gaps requires detailed, practice-level analysis, stronger causal estimation methods, a broader geographic scope, and explicit connections between GAPs adoption, productivity, and market performance.

2.6 Conceptual framework

In the present study, the conceptual framework (Figure 2.1) illustrates the relationships between key independent variables, namely farm size, exposure to training on GAPs, and contractual arrangements with exporter companies, which is the adoption of Good Agricultural Practices (GAPs). GAPs are conceptualized along the production cycle, including pre-harvest practices (soil testing, use of certified seedlings, pruning, integrated pest management, irrigation, fertilizer application, and mulching), harvest practices (use of recommended tools, harvesting at physiological maturity, and avoiding fruit drop), and post-harvest practices (sorting/grading, use of crates, pre-cooling, proper packaging, and traceability).

The framework further posits that the adoption of GAPs influences market outcomes, particularly post-harvest quality and the share of the avocado harvest exported. These outcomes are reflected in variables such as the proportion of the harvest accepted at packhouses, the price received per kilogram, the share of production sold to high-value markets, rejection rates, and household income from avocado sales. By treating GAPs adoption as the dependent variable, the framework emphasizes that the effects of farm size, training, and contracts on market performance are mediated by the extent to which farmers adopt recommended practices. Figure 2.1 presents the conceptual framework linking socio-economic, institutional, and farm-level factors to GAPs adoption.

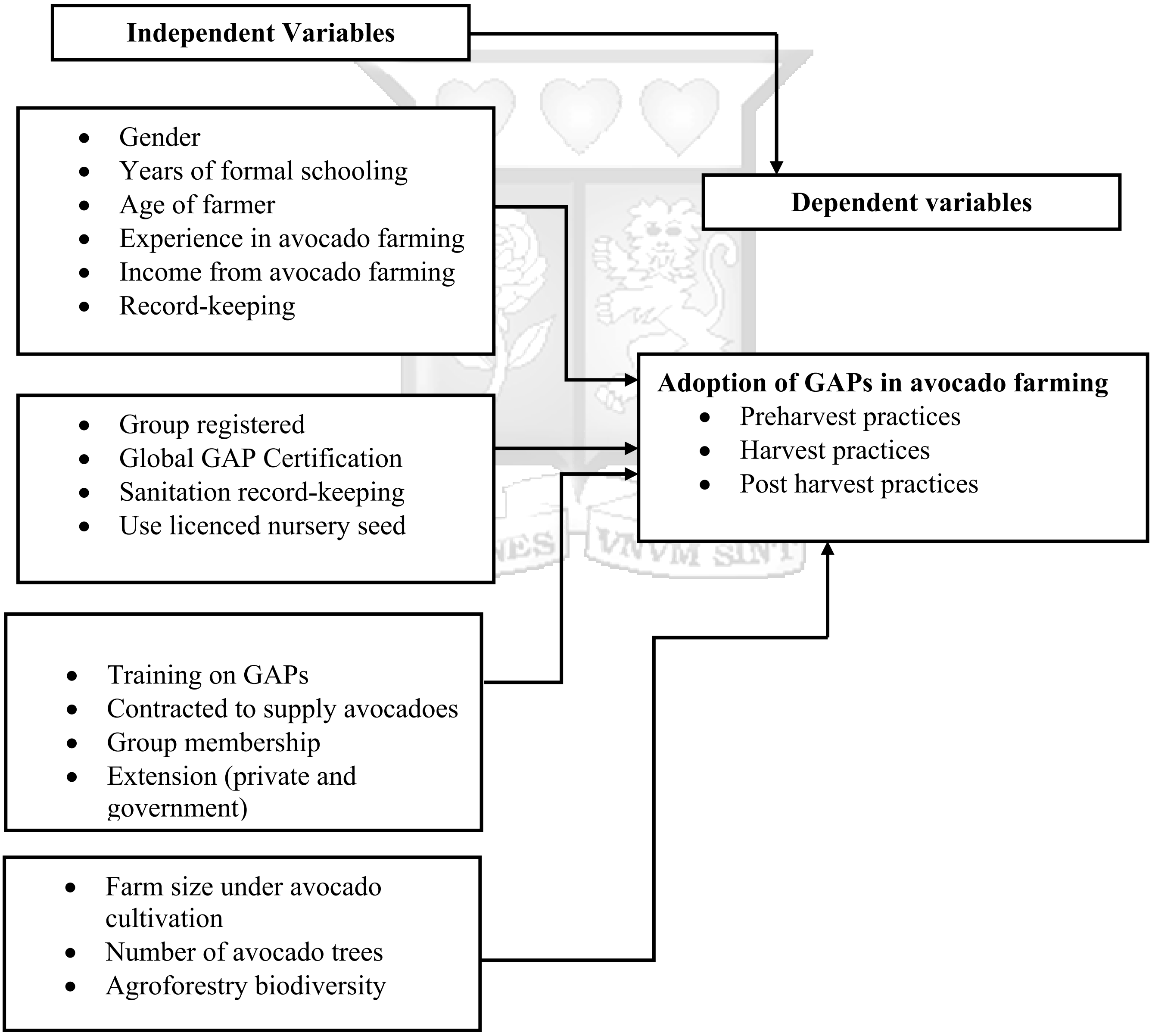

Figure 2.1: Conceptual Framework
Source: Author's Conceptualization

2.7 Operationalization of the study variables

This study examined the influence of household characteristics, household resource base, institutional characteristics, and avocado farming characteristics on the adoption of Good Agricultural Practices (GAPs) among avocado farmers in Murang'a County, Kenya. The independent variables included household characteristics (gender, years of formal schooling, age of farmer, and experience in avocado farming), household resource base (income from avocado farming and record keeping), institutional characteristics (training on GAPs, contract to supply avocados, and group membership), and avocado farming characteristics (farm size under avocado cultivation and number of avocado trees), while the dependent variable was the adoption of GAPs in avocado farming, disaggregated into preharvest, harvest, and post-harvest practices. Table 2.2 provides a breakdown of the variable indicators and the measure of each study variable, where in this case the research used binary response options (1 = Yes, 0 = No) to capture adoption of individual GAPs, continuous measures for farm-level and socioeconomic variables, and dummy variables for categorical institutional characteristics.

Table 2.2: Operationalization of the Study Variables

Variable Name	Variable Indicators	Measurement	Source of Data
DEPENDENT VARIABLE: Adoption of Good Agricultural Practices (GAPs) in Avocado Farming			
Preharvest Practices	Sanitation records maintained; Prompt elimination of dropped fruits; IPM program implementation; Pest monitoring; Fruit fly & False Codling Moth control; Bi-weekly monitoring of quarantine pests; Immediate pest control measures; Use of approved pesticides; Correct pesticide dosage application	Binary (1=Yes, 0=No) for each practice. A composite preharvest GAPs adoption score is computed from individual practice adoption indicators.	Secondary Data from Cross-sectional survey of 2025, a structured household survey questionnaire administered to avocado farmers in Murang'a County
Harvest Practices	Use of clean harvesting tools; Hand-picking of avocados; Use of poles with baskets for harvesting	Binary (1=Yes, 0=No) for each practice. A composite harvest GAPs adoption score is derived from individual indicators.	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire administered to avocado farmers in Murang'a County
Post-harvest Practices	Proper storage of produce; Washing of produce; Use of crates for handling/transport; Sorting of produce; Proper disposal of waste; Compliance with pesticide withdrawal period (REI/PHI)	Binary (1=Yes, 0=No) for each practice. A composite post-harvest GAPs adoption score is computed from individual practice adoption indicators.	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire administered to avocado farmers in Murang'a County
INDEPENDENT VARIABLES, Household Characteristics			
Gender	Sex of household head / farm operator	Dummy variable: 1 = Male, 0 = Female	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire
Years of Formal Schooling	Highest level of education attained (None, Primary, Secondary, Tertiary, Postgraduate)	Ordinal scale: 0 = No formal education; 1 = Primary; 2 = Secondary; 3 = Tertiary; 4 = Postgraduate. Number of years of schooling recorded as continuous variable.	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire

Age of Farmer	Age of the household head / farm operator at the time of the survey	Continuous variable measured in years	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire
Experience in Avocado Farming	Number of years the farmer has been growing avocados	Continuous variable measured in years (mean = 13.83 years; range: 2–44 years)	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire
INDEPENDENT VARIABLES, Household Resource Base			
Income from Avocado Farming	Gross household income earned from sale of avocados in the last and current seasons	Continuous variable measured in Kenya Shillings (KES). Log transformation applied where appropriate to normalize distribution.	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire
Record Keeping	Farm logs; Harvest records; Hygiene records; Pest control records; Input records; PPE cleaning records; Sales records; Training records; Waste disposal records	Binary (1=Yes, 0=No) per record type. A composite record-keeping index may be derived from the number of record types maintained.	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire
INDEPENDENT VARIABLES, Institutional Characteristics			
Training on GAPs	Receipt of training in Good Agricultural Practices, SPS compliance, certification compliance, post-harvest management, market access, and record keeping; training provider (private sector, government, NGO/cooperative)	Binary (1=Yes, 0=No). Training timeframe captured for the last 6 and 12 months. The type of training provider is also recorded as a categorical variable.	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire
Contracted to Supply Avocados	Existence of a formal contractual arrangement with an exporter/buyer for supply of avocados	Dummy variable: 1 = Has a contract with exporter/buyer, 0 = No contract	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire

Group Membership	Membership in a farmer group, cooperative, or association involved in avocado production or marketing	Dummy variable: 1 = Member of a farmer group/cooperative, 0 = Not a member	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire
INDEPENDENT VARIABLES, Avocado Farming Characteristics			
Farm Size under Avocado Cultivation	Area (in acres) of the farm dedicated specifically to avocado cultivation	Continuous variable measured in acres (acres; range: Log-transformed in regression models.	Secondary Data from Cross-sectional survey of 2025, structured household survey questionnaire
Number of Avocado Trees	Total number of avocado trees on the farm	Continuous variable measured as count of trees. Log transformation applied where appropriate.	Secondary Data from the Cross-sectional survey of 2025, structured household survey questionnaire

Source: Compiled by the author based on the study's conceptual framework and Secondary Data from a cross-sectional survey of 2025 survey data of Murang'a County, Kenya

2.8 Chapter summary

Chapter Two provided the theoretical and empirical foundation underpinning the study on the adoption of Good Agricultural Practices (GAPs) among avocado farmers in Murang'a County, Kenya. The chapter opened by grounding the study in three complementary theoretical frameworks. The Theory of Planned Behaviour (TPB) was used to explain how farmers' attitudes toward GAPs, social pressures from exporters and cooperatives, and perceived ability to comply jointly shape adoption intentions and actual behaviour. The Random Utility Theory (RUT) provided the microeconomic foundation for modelling farmers' discrete adoption choices, recognising that farmers select practices that maximise their perceived utility, while accounting for unobserved heterogeneity in risk preferences, farm conditions, and market access.

The Diffusion of Innovations (DoI) Theory complemented these by explaining how GAPs, as a multi-component standard, spread through farmer networks, extension systems, and export-chain institutions over time, with adoption rates shaped by perceived attributes of the innovation such as relative advantage, compatibility, complexity, trialability, and observability. Together, these three theories offered a holistic lens that addressed the behavioural, economic, and social dimensions of GAPs adoption simultaneously. The empirical literature review synthesised evidence from studies on standards compliance and GAPs adoption across horticultural value chains, with particular attention to Kenyan contexts. Findings consistently showed that farm size, access to training, exporter contracts, group membership, and household wealth are key drivers of adoption, while post-harvest practices remain the most poorly adopted and least studied component.

Methodologically, the review critically noted that most existing studies aggregate adoption into a single compliance score, rely on cross-sectional probit or logit models, and fail to account for the joint and interdependent nature of multi-stage GAPs adoption, thereby limiting the depth and causal rigour of their conclusions. The multivariate probit (MVP) model was identified as the most appropriate analytical framework for the current study, given its ability to model simultaneous adoption decisions across pre-harvest, harvest, and post-harvest stages while capturing inter-practice correlations. The chapter further identified several empirical gaps in the existing literature, including the absence of Murang'a-specific avocado evidence, weak causal identification of adoption determinants, limited disaggregation of adoption by practice type, and insufficient linkage between specific GAPs practices and measurable market outcomes.

These gaps directly informed the design and objectives of the current study. The chapter concluded by presenting the conceptual framework, which illustrated how farm size, training, and exporter contracts influence GAPs adoption across the three production stages, and how adoption in turn affects market outcomes including export share, packhouse acceptance rates, and household income. The operationalization of variables was also detailed, specifying how each independent and dependent variable was measured using binary, continuous, and dummy indicators drawn from a structured household survey.

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CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the study's assessment of the factors influencing the uptake of Good Agricultural Practices (GAPs) among avocado farmers in Kenya. It details the research paradigm, design, study population, sampling procedures, and data collection process using KoboToolbox. The chapter further explains how the study ensured reliability and credibility, formulated the empirical framework, defined and measured variables, conducted data analysis, and adhered to ethical standards.

3.2 Research philosophy

This study is anchored in pragmatism, a research philosophy that prioritises the practical adequacy of methods for answering specific research questions over allegiance to a single epistemological position (Kaushik & Walsh, 2019; Sciberras & Dingli, 2023). Pragmatism holds that the value of a research design lies in its capacity to generate useful, actionable knowledge, and it explicitly accommodates the combination of quantitative and qualitative approaches within a single study where doing so improves the quality of evidence (Creswell & Creswell, 2018; Huyler & McGill, 2019). This contrasts with positivism, which presumes a single objective reality measurable through hypothesis testing alone, and with interpretivism, which treats reality as socially constructed and privileges subjective meaning (Keong Yong *et al.,* 2021; Open University, 2016). While elements of both traditions are present in the design, for example, the use of structured survey instruments and econometric estimation reflects a broadly positivist orientation toward measurement and generalisable patterns, the overall research strategy is better characterised as pragmatic because methodological choices were driven primarily by their fitness for answering the study's objectives rather than by adherence to positivist assumptions of strict causal identification.

The study sought to characterise avocado farmers and examine the associations between farm size, GAPs training, exporter contracts, and the adoption of pre-harvest, harvest, and post-harvest GAPs. Answering these questions required quantitative measurement of adoption levels and explanatory factors across a large sample, complemented by brief open-ended qualitative probes to contextualise and enrich the interpretation of statistical patterns. Pragmatism is therefore the philosophical foundation most consistent with this combination of quantitative breadth and qualitative depth, and it directly informs the mixed-methods research design adopted (Baert, 2004; Mbanaso *et al.,* 2023).

3.3 Research design

Research design is the overall strategy that links the research questions to the methods used for data collection, analysis, and interpretation (Capili, 2021). Consistent with the pragmatist philosophy, this study adopted a cross-sectional mixed-methods explanatory design, combining a structured quantitative survey with brief open-ended qualitative probes (Creswell & Creswell, 2018; Kaushik & Walsh, 2019). A mixed-methods approach was methodologically appropriate, not merely convenient, because the research objectives required both the statistical estimation of relationships between farm-level characteristics and GAPs adoption, and contextual insight into why farmers adopt or fail to adopt specific practices, insight that quantitative indicators alone could not capture (Tobi & Kampen, 2018).

The quantitative component followed a cross-sectional explanatory (correlational) design, in which data on GAPs adoption and its hypothesised determinants, farm size, training exposure, and exporter contracts, were collected from a representative sample of avocado farmers at a single point in time (Pirasath *et al.,* 2020). An explanatory cross-sectional design was selected over a purely descriptive one because the study's objectives go beyond characterising adoption levels; they require testing associations between specific farm-level and institutional factors and the probability of adopting GAPs across the pre-harvest, harvest, and post-harvest stages. The multivariate probit framework employed is well suited to this explanatory, associational objective, as it estimates the strength and direction of relationships between covariates and adoption decisions while accounting for correlations across the three adoption outcomes (Cappellari & Jenkins, 2003).

It is important to note that, given the cross-sectional nature of the data, the relationships estimated in this study are interpreted as statistically significant associations rather than as definitive causal effects. The multivariate probit model controls for a wide range of observable household, farm, and institutional characteristics, which reduces, though does not eliminate, the influence of confounding factors on the estimated relationships (Wooldridge, 2012). The possibility that unobserved factors jointly influence both the explanatory variables of interest (particularly training exposure and exporter contracts) and GAPs adoption, for instance, through farmer self-selection into training or contracting arrangements, is acknowledged as a limitation of the cross-sectional design. A cross-sectional design was nonetheless considered the most suitable approach for this study, both methodologically, because it allows simultaneous measurement of adoption across multiple GAPs domains and a broad set of explanatory factors within a single survey round (Yin *et al.,* 2023), and practically, because it offered an efficient and cost-effective means of generating policy-relevant evidence within the available resources (Blair *et al.,* 2023). Comparable approaches combining quantitative cross-sectional analysis with qualitative elements have been used effectively to examine smallholder adoption behaviour among Kenyan avocado farmers (Inoti & Nkurumwa, 2023). Data were collected using a structured KoboToolbox questionnaire, with embedded open-ended questions providing qualitative context for the quantitative findings.

3.4 Research study area and population

3.4.1 Target population

The target population refers to the complete set of units about which the study seeks to draw conclusions, and from which the sample was drawn (Asiamah *et al.,* 2017). For this study, the target population comprised smallholder and medium-scale avocado farming households in Murang'a County, Kenya, specifically those located in the major avocado-producing sub-counties (Kiharu, Kandara, Kigumo, Kangema, Murang'a South, Gatanga, and Mathioya) who grow avocado commercially and sell some portion of their harvest through local markets, brokers, cooperatives, or export agents.

Based on county agricultural production records, the target population was estimated at 120,000 avocado-farming households in Murang'a County (USDA, 2026). Murang'a County accounts for an estimated 20-40% of Kenya's national avocado output depending on the year and metric (USDA, 2025b, 2026), and production remains overwhelmingly smallholder-driven, with farms of less than 5-10 a85%r roughly 85% of national output (N. Kamotho *et al.,* 2023). This figure of 120,000 households formed the sampling frame population (N) used in the sample size calculation.

The qualitative component of the study did not draw on a separately defined population or sample. Rather than employing dedicated qualitative tools such as focus group discussions or key informant interviews, qualitative data were generated through brief open-ended questions embedded within the same structured KoboToolbox questionnaire administered to the quantitative sample. Consequently, the qualitative probes drew on responses from the same 698 farmers who completed the quantitative survey, providing contextual narrative to complement, rather than independently sample from, the quantitative findings. This integrated approach is consistent with the pragmatist, mixed-methods design described in, though it represents a more limited qualitative strand than would be obtained through a separately sampled qualitative component.

3.4.2 Study area

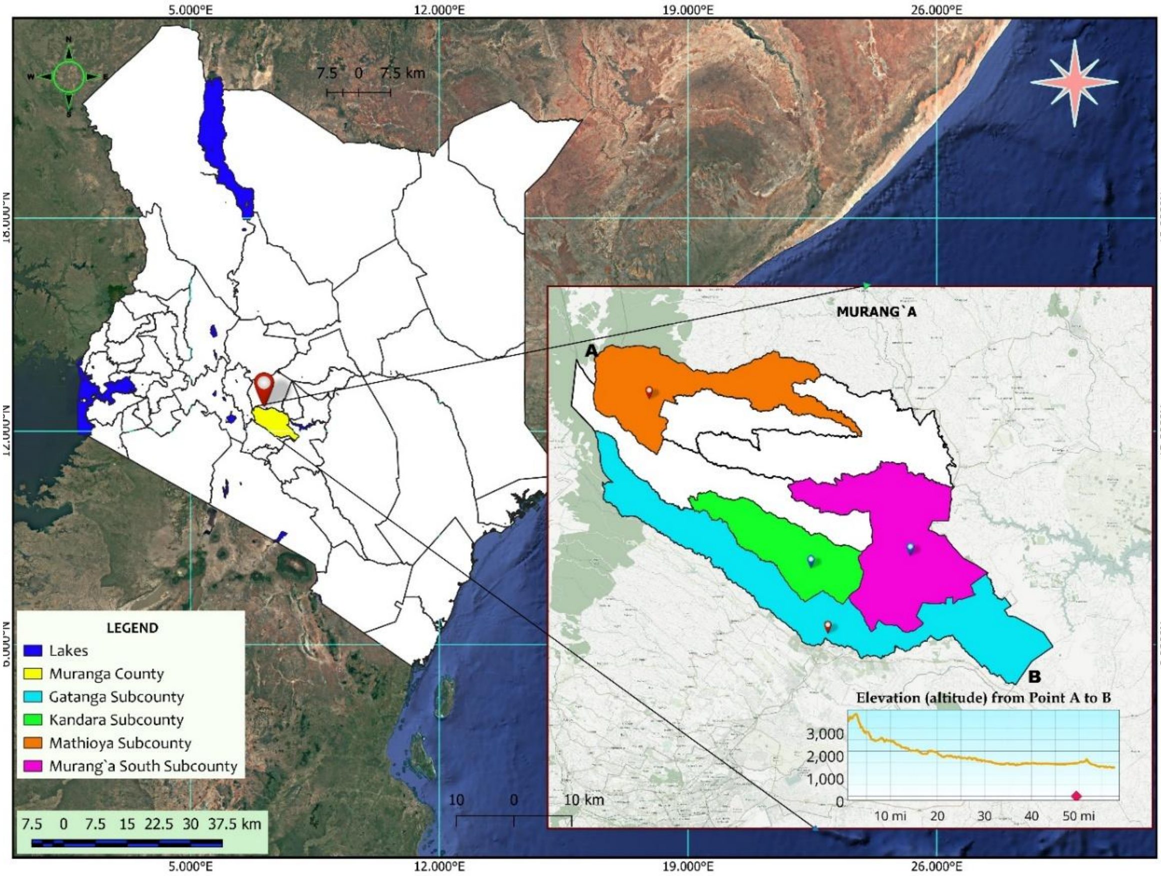

Figure 3.1: Map of the study area

Source: Authors Q-GIS Maps (2026)

Key production sub-counties include Kiharu (Murang'a East), Kandara, Kigumo, Kangema, and surrounding high-potential zones. These areas feature established farmer cooperatives such as the Murang'a Avocado Farmers Cooperative Union, packhouses, aggregation centres, and strong linkages to both domestic and export markets (Kenya News Agency, 2025b, 2025a). These zones were selected for their high production volumes, active commercial orientation (including exports), and documented challenges relating to post-harvest losses (Muita *et al.,* 2025), transactional costs and export participation (Karing'u *et al.,* 2021), and collective marketing and technology adoption (Kwizerimana *et al.,* 2023). Prior studies drawing samples from these sub-counties confirm Murang'a as a suitable site for examining GAPs adoption. Capacity-building efforts have also been ongoing in the county to strengthen the use of biopesticides and integrated pest management among avocado farmers (Agro reports abroad, 2026).

3.5 Sampling technique and sample size calculation

The target population for this study was 120,000 avocado farmers in Murang'a County (USDA, 2026). The sample size was determined using Yamane's formula (Yamane, 1967):

$$n = \frac{N}{1 + N(e)^2}$$

Where: n= Sample size, N= Population size (120,000) and e= Margin of error. The study adopted a margin of error of 3.7% was applied at a 95% confidence level. This yielded:

$$n = \frac{120{,}000}{1 + 120{,}000(0.037)^2} \approx 725$$

A 3.7% margin of error was considered appropriate for this study because it provides a good balance between statistical precision and practical feasibility. While a 5% margin of error is commonly used in social sciences, a tighter margin (3.7%) was adopted to increase the precision and reliability of the findings, given the large target population and the need for more representative results on avocado farming practices in Murang'a County. The qualitative component did not involve a separate sample size calculation, since the open-ended probes were administered to the same 698 respondents.

Table 3.1: Distribution of the sample size

	% of sample size	**No. of farmers**
Main study	90	653
Pilot study	10	72
Total	**100**	**725**

Source: Researcher (2025)

3.5.2 Sampling procedure and representativeness

A multi-stage sampling approach was used to select respondents. First, avocado-producing sub-counties were purposively selected based on county production records and the presence of exporter collection hubs, namely Kiharu, Kandara, Kigumo, Kangema, Murang'a South, Gatanga, and Mathioya. Second, wards and villages with high avocado activity within each selected sub-county were randomly sampled. Third, a sampling frame of avocado farmers was constructed from lists provided by county agriculture offices, farmer cooperatives, and exporter collection centres, from which households were randomly selected to reach the target sample size. While this multi-stage approach is statistically grounded, the achieved sample exhibits a marked geographic imbalance: 83.24% of completed responses (n = 581) originate from Kandara sub-county alone, with the remaining sub-counties, Murang'a South (10.32%), Gatanga (5.16%), Mathioya (1.00%), Kangema (0.14%), and Murang'a East (0.14%), together accounting for less than 17% of the sample (Table 4.2). This concentration likely reflects the distribution of the sampling frame itself, as Kandara hosts a particularly dense concentration of avocado cooperatives, packhouses, and exporter collection centres from which farmer lists were drawn (Kenya News Agency, 2025), making it both the most accessible and most commercially active sub-county for sample frame construction.

This imbalance has implications for the representativeness and external validity of the findings. Estimates from this study should be interpreted as most representative of avocado farming conditions in Kandara, where commercial orientation, exporter linkages, and GAPs-related institutional support are comparatively well developed and may not generalise fully to farmers in less commercially integrated sub-counties such as Mathioya, Kangema, or Murang'a East, where access to training, contracts, and extension services may differ substantially. To the extent that Kandara farmers are more exposed to exporter contracts and training opportunities, the study's estimates of the effects of these institutional factors on GAPs adoption may be more applicable to commercially integrated production zones than to the county as a whole. This limitation is revisited in the discussion of the study's limitations.

3.6 Data collection methods

This study used quantitative secondary data obtained from a baseline survey of the avocado sector in Kenya, conducted in 2025 by Mavuno/KTL and The Fresh Produce. The unit of analysis was the individual avocado-farming household (specifically, the household head or primary avocado farm manager responsible for orchard management, input use, and marketing decisions), meaning that all variables, estimation, and interpretation in this study are at the farm/household level rather than the plot, exporter, or cooperative level. Data were collected electronically via KoboToolbox on tablets and smartphones, enabling structured entry, skip logic, GPS-stamping, and real-time uploads to a central server. Before the main survey, a pretest was conducted with 73 avocado farmers from areas outside the sampled sub-counties to assess question clarity, survey flow, and cultural appropriateness, and enumerators received structured training in research ethics, interview techniques, and electronic data collection.

The questionnaire captured data using a mix of measurement scales appropriate to each construct. Binary (dichotomous) scales were used for yes/no indicators such as GAPs adoption (pre-harvest, harvest, post-harvest), training participation, group membership, contract status, and record-keeping. Ordinal scales were used for variables such as education level (categorised from none to tertiary and above). Continuous (ratio/interval) scales were used for variables such as farm size (acres under avocado), number of avocado trees, age, years of farming experience, household income, yield per tree, proportion of Grade 1 produce, and export share. Categorical (nominal) scales were used for variables such as training provider type (private sector, government, NGO/cooperative) and sub-county of residence.

The questionnaire covered four broad domains: (i) socio-demographic attributes (age, gender, education level, farming experience); (ii) farm profile characteristics (land size, number of avocado trees); (iii) Good Agricultural Practices components across the three production stages (pre-harvest practices such as Integrated Pest Management and use of certified planting material; harvest practices such as hand-picking and harvest timing; and post-harvest practices such as grading, hygienic handling, and record-keeping); and (iv) institutional and market engagement variables, including capacity-building participation (training attendance by timeframe, frequency, and provider), formal contractual arrangements with exporters, and farm performance indicators (yield per tree, proportion of Grade 1 fruit, post-harvest losses, and export share).

Prior to use of the data, the researcher obtained an introductory letter from the university, an ethical approval certificate, and a research licence from the National Commission for Science, Technology, and Innovation (NACOSTI-Ref. No. 629894). Informed consent had been obtained from the 698 farmers by the original data collection team, and the researcher additionally briefed county agricultural officers and cooperative leaders on the objectives of the current study to ensure transparency in its use.

3.7 Research quality

Before conducting the main survey, the researcher carried out a pilot study to refine and enhance the research instruments. This preliminary exercise enabled an assessment of the reliability, validity, and clarity of the data collection tools, ensuring that they effectively capture the intended information and function as expected during the full-scale data collection process (Vogel and Draper-Rodi, 2017). Its goal is to find and correct any errors, ambiguities, or issues in the questionnaire to ensure smooth implementation of the main study. For this purpose, 73 avocado smallholder farmers were randomly selected to participate in the pilot test. Their feedback helped refine question wording, flow, and clarity, and also assessed the functionality of the KoboToolbox platform in the field. Responses from the pilot data were not used in the final analysis to prevent any bias.

3.7.1 Validity of research instruments

Validity pertains to how well a research instrument accurately measures the intended construct, thereby providing relevant and truthful information about the subject being studied (Mohajan and Mohajan, 2017). To ensure face validity and content validity, a pilot study was conducted following established best practices (Friedel *et al.,* 2021) as noted in prior methodological research. Academic supervisors, along with experts in agricultural economics and research methods, reviewed the questionnaire items to ensure they fully address the study's objectives and are suitable for smallholder avocado farming. Feedback from pilot participants and expert reviewers was integrated to improve the instrument's clarity, relevance, and comprehensiveness.

Table 3.2: Validity Results of Research Instruments

Variable	KMO	Approx. Chi-Square	df	Significance	Conclusion	Validity
Pre-Harvest GAP Practices (12 items)	0.629	4704.93	66	0	Significant	Valid for factor analysis
Harvest GAP Practices (2 items)	0.5	—	—	—	Marginal adequacy	Limited validity
Post-Harvest GAP Practices (6 items)	0.631	831.182	15	0	Significant	Valid for factor analysis

Source: Data (2025)

The KMO values for all constructs range between 0.500 and 0.631, indicating marginal to mediocre sampling adequacy according to Kaiser’s criteria (Kaiser, 1974). This confirms that the data is suitable for factor analysis, although some constructs demonstrate weaker adequacy, particularly the harvest GAPs construct. The Bartlett’s Test of Sphericity is statistically significant ($p < 0.05$) for both pre-harvest and post-harvest constructs, indicating that the variables are sufficiently correlated to proceed with factor analysis. However, the harvest construct shows limited validity due to its reduced number of items, which limits its statistical power. The constructs are considered acceptable for further analysis, with stronger validity observed for the pre- and post-harvest GAP practices than for the harvest construct.

3.7.2 Empirical Assessment via KMO and Bartlett's Test

To empirically assess the construct validity and sampling adequacy of the questionnaire, the study employed the Kaiser-Meyer-Olkin (KMO) statistic and Bartlett's Test of Sphericity. These tests helped determine whether the data are suitable for factor analysis and whether the questionnaire items effectively represent the underlying constructs being measured (Zhang *et al.,* 2024). These tests assessed whether the items are appropriate for factor analysis and effectively capture the underlying constructs. A KMO value near 1.0 indicates excellent suitability, whereas values below 0.5 are considered unsatisfactory (Shrestha, 2021).

3.7.3 Reliability of research instruments

Reliability refers to how consistently a research instrument produces the same results when used repeatedly under similar conditions (Andrade, 2019). In this study of avocado smallholder farmers, reliability ensures that the questionnaire yields stable, consistent responses across farmer groups and over time. Locharoenrat (2017) Suggests that an adequate pilot test sample should be about 10% of the total study sample. Consequently, this study tested reliability using a pilot sample of 73 avocado farmers, representing 10% of the total target sample of 725 respondents, as determined by Cochran's formula. A total of 73 pilot questionnaires were administered, and the collected data were entered into Stata version 17 for analysis. Microsoft Excel was also used to generate graphical representations, such as charts and pie charts. To evaluate the instrument's internal consistency, the study computed Cronbach's alpha. This statistic, widely applied in agricultural and social science research, serves as a key indicator of the reliability and internal coherence of questionnaire items (Jain and Angural, 2017; Taber, 2018).

According to Chan and Idris (2017) For newly designed instruments, a Cronbach's alpha coefficient of 0.70 or higher is considered satisfactory, underscoring the importance of this criterion for establishing the reliability of measurement tools in field-based research. As outlined by Taber (2018), the conventional interpretation of Cronbach's alpha values is as follows: >0.9 (Excellent), >0.8 (Good), >0.7 (Acceptable), >0.6 (Questionable), >0.5 (Poor), and <0.5 (Unacceptable). These reference points served as the basis for evaluating the dependability and internal coherence of the questionnaire employed in this study. The internal consistency of the three Good Agricultural Practices (GAPs) scales was assessed using Cronbach's alpha. As shown in Table 3.3, the Pre-Harvest GAPs scale, consisting of 9 items, achieved a Cronbach's alpha of 0.81, indicating good reliability. The Harvest GAPs scale (2 items) yielded an alpha of 0.74, which is considered acceptable reliability given the small number of items. The Post-Harvest GAPs scale (5 items) recorded a Cronbach's alpha of 0.79, also falling within the acceptable reliability range. These values exceed the commonly recommended threshold of 0.70 (Nunnally & Bernstein, 1995), confirming that all three scales possess sufficient internal consistency for subsequent analysis.

Table 3.3: Reliability results of research instruments

Variable	Cronbach's Alpha	Number of Items	Interpretation
Pre-Harvest GAPs	0.81	9	Good reliability
Harvest GAPs	0.74	2	Acceptable reliability
Post-Harvest GAPs	0.79	5	Acceptable reliability

Source: Survey Data (2025)

3.8 Data analysis and presentation

The study employed both descriptive and econometric methods to analyze the data. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarize farmers' socio-demographic characteristics, farm attributes, and the extent of their adoption of Good Agricultural Practices (GAPs[1]). The results were presented clearly through graphs and tables. Additionally, t-tests and chi-square tests of differences were conducted to assess the models for differences in GAPs adoption across outcomes such as yield, quality (Grade 1 classification), post-harvest losses, and export proportions, while controlling for potential selection bias. To meet the study's objectives, econometric models were applied. Since GAPs adoption is a binary outcome (adopter = 1, non-adopter = 0), binary probit models and Multivariate Probit models were used to analyze how farm characteristics, training, and contracts influence adoption decisions.

3.8.1 Objective 1: To characterize avocado farmers in Kenya

Descriptive analysis. For Objective 1 (characterising avocado farmers and their compliance levels), the study generated frequency tables, percentages, means, and standard deviations for socio-demographic, farm-level, and institutional variables. The resulting dataset is a set

[1] The GAPS and their categories are displayed in the Appendix 1

of summary tables and figures describing the sample's characteristics and the prevalence of adoption for each GAPs across the three stages. Interpretation of these descriptive results assumes that the sample, despite the geographic concentration provides a reasonably accurate picture of farming conditions in the commercially active sub-counties from which most respondents were drawn, and findings are presented with this caveat in mind.

Bivariate analysis. To assess differences in outcomes (yield, Grade 1 share, post-harvest losses, export share) between GAPs adopters and non-adopters, independent-samples t-tests were used for continuous variables and chi-square tests of independence for categorical variables. The resulting output is a set of comparison tables reporting group means/proportions, test statistics, and p-values. Interpretation assumes that the t-test's underlying assumptions, approximately normal distributions of the continuous variable within each group, or a sufficiently large sample size for the Central Limit Theorem to apply, and independence of observations, are reasonably met; where continuous variables were found to be markedly non-normal, this is noted alongside the t-test results.

3.8.2 Objective 2: Empirical Models: factors influencing GAPs adoption

From the Random Utility Theory (RUT[2]), the Probit model is developed on the premise that farmers are likely to adopt Good Agricultural Practices (GAPs) only when the perceived utility of adoption exceeds that of non-adoption. Using the Probit framework enables this study to capture potential associations and interdependencies among categories of avocado GAPs. In this analysis, the model incorporated three binary outcome equations that represent the adoption of pre-harvest, harvest, and post-harvest GAPs. Because these practices are assumed to be mutually dependent, assessing adoption behavior using a discrete choice model without accounting for potential error covariances would result in biased and inconsistent estimates. In line with Davis *et al.* (1998), the utility U_{ij}that the *i-th* avocado farmer obtains from adopting a specific GAP (*j*) is defined as a linear combination of two components: a deterministic term (V_{ij}), reflecting the observable factors influencing the decision, and a stochastic disturbance term (ε_i), representing the unobserved influences and measurement inaccuracies. This relationship is specified in Equation 3.1.

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad (3.1)$$

For binary choices regarding the adoption of avocado GAPs, see Equation 3.2.

[2] This is comprehensively discussed in the Theoretical framework as the overarching theory of the study

$$y_{ij} = x_{ij}\beta + \varepsilon_{ij} \tag{3.2}$$

Where yi is the adoption decision; x=regressors; β=parameter estimates; and ε=stochastic error term, which considers the combined effects of the variables. In decision modeling, this stochastic residual captures the combined influence of multiple factors that may introduce uncertainty into the decision-making process. Farmer *i* faces two possible alternatives, *j* and *k*, and the corresponding utilities associated with these choices are represented by U_{ij} and U_{ik} (Greene, 2005).

U_{ij}: Utility derived from adopting a set of GAPs.

U_{ik}: Otherwise

$$U_{ij} = X\beta_{ij} + G_{ij}\gamma_{ij} + \varepsilon_{ij} \tag{3.3}$$

In Equations (3.3) and (3.4), denotes the measurable characteristics of the farmer, such as landholding size, access to financial services, and educational attainment. G signifies the features of the available alternatives (adoption: j or non-adoption: k), where the avocado farmer decides whether or not to implement a specific management practice. εrepresents the unobserved components of utility not captured by the researcher. A farmer opts to adopt GAPs (Y = 1) if $U_{ij} > U_{ik}$, and chooses not to adopt (Y = 0) if $U_{ij} < U_{ik}$.

$$U_{ik} = X\beta_{jik} + G_{ik}\gamma k + \varepsilon_{jik} \tag{3.4}$$

A farmer's decision is not entirely predictable since the error component is unobservable. According to Greene (2003), the likelihood of selecting a particular option is expressed as shown in Equation 3.5, where U_{ij} and U_{ik} denote the utilities associated with alternatives *j* and *k*, respectively, for farmer *i.*

$$P(Y = 1) = U_{ij} > U_{ik}|X_i \tag{3.5}$$

To examine the influence of farm size and other characteristics on the probability of GAPs adoption, for one practice, the following binary probit model was specified in Equation 3.6: $P(GAP\_adopti = 1) = \Phi(\beta 0 + \beta 1 FarmSizei + \beta 2 Trainingi + \beta 3 Contractsi + \beta 4 X4 + \epsilon i)$ (3.6)

Where $P(GAP\_adopti = 1)$ represents the likelihood that farmer *i* adopts a particular Good Agricultural Practice (GAPs). Φdenotes the cumulative distribution function of the standard normal distribution, while $\varepsilon_i$signifies the stochastic disturbance term. In this case, since there were three GAPs categorized as Preharvest practices, Harvest practices, and Post-harvest practices, a farmer might have adopted three of them simultaneously; therefore, a Multivariate probit model was better suited for the analysis. The study assessed how farm size differentially affects each GAPs.

The Multivariate Probit (MVP) model is equally reliable, generating estimates that are consistent, efficient, and unbiased (Assaye *et al.,* 2023; Bwiza *et al.,* 2024). Numerous empirical studies have employed the MVP and related econometric models to investigate the determinants of the adoption of integrated pest and disease management practices. The present study adopts a similar analytical framework, recognizing that Good Agricultural Practices (GAPs) are often adopted concurrently rather than independently. Several studies[3] assumes that a farmer selects multiple strategies *j* at time *t* to maximize overall utility within the limits of available resources.

$$Max\ U_{it} = f(X_{it}) \tag{3.7}$$

Where *X* is a vector of explanatory variables influencing the adoption decision of the farmer, an avocado-producing household would consider adopting a set of GAP strategies if $Y = 1$ if $U_{ij} > Uik$ and $Y = 0$ if $U_{ij} < U_{ik}$.. When the anticipated utility derived from adoption exceeds that from non-adoption, and given that this utility is not directly observable, it can be represented through the following latent variable framework.

$$Y^* = Y\ =\ 1\ if\ \ U_{ij} > U_{ik}\ \ and\ Y\ =\ 0\ if\ U_{ij} < U_{ik} \tag{3.8}$$

Because $Y^*_{itm}$is an unobserved (latent) variable, its empirical representation is estimated as a binary outcome, expressed as follows:

$$Y^*_{itj}\ =\ \beta X_{itj}\ +\ \mu\ \ where\ \ Y_{itj} = \{1,\ andif Y^*_{ij} > 0\ 0,\ and\ otherwise\ \ j = 1,2,..j \tag{3.9}$$

Following Cappellari and Jenkins (2003) in line with the utility function presented in Equation 3.9, a Multivariate Probit (MVP) model comprising three dependent variables, $y_1, \dots, y_m$, can be formulated. Here, $i = 1, \dots, 3$represents the various GAPs, while $j = 1, \dots, n$and $n$indicate the total sample size. Similarly, consistent with the utility framework in Equation 3.7 and following the approach outlined in *(ibid)*, the MVP model with three dependent variables can be specified as shown in Equation 3.12.

[3] The studies have been discussed comprehensively in the empirical literature review section.

$$Y_{ij}^{*} = x_{ij}'\beta_j + \varepsilon_{ij}, \qquad j = 1, \dots\dots..n \tag{3.10}$$

$$Y_{ij} = \{1, \ and if Y_{ij}^{*} > 0 \ 0, \ \text{and otherwise} \tag{3.11}$$

$$\begin{cases} y_{i1} \\ y_{i2} = \beta_0 + \beta 1 FarmSizei + \beta 2 Trainingi + \beta 2\ Contractsi \dots + \beta_{vn} X_{vn} + \varepsilon_{1\dots\dots3,} \\ y_{i3} \end{cases} \tag{3.12}$$

Where y_1, y_2, y_3 represent the respective GAPs; $X_1, \dots, X_n$ denote the explanatory variables that affect the adoption decision; and $\beta_1, \dots, \beta_n$ are the parameters to be estimated. ε signifies a random disturbance term, while $\varepsilon_{(1\dots3)}$ correspond to the error components associated with each of the three equations. The latent variables are presumed to jointly follow a Multivariate Normal (MVN) distribution across equations, characterized by a zero conditional mean and a variance normalized to one, specifically, $(u_{\text{Preharvest GAPs}}, u_{\text{Harvest GAPs}}, u_{\text{Postharvest GAPs}}) \sim MVN(0, \Omega)$. Here, Ω represents the covariance matrix of X. Additional variables are incorporated into the model to account for heterogeneity among farmers, as outlined in Table 3.1.

$$\Omega = \begin{bmatrix} 1 & \rho & \rho \\ \rho & 1 & \rho \\ \rho & \rho & 1 \end{bmatrix} \tag{3.13}$$

Where ρ represents the pairwise correlation coefficient of any two GAPs corresponding to the error terms. The use of a multivariate probit rather than a univariate probit for each unique GAPs is justified if these correlations in the off-diagonal elements of the covariance matrix become nonzero. Prior to the analysis, a pairwise correlation analysis of the dependent variable was conducted to test whether an MVP is justified; if not significant, a single Probit model was then used. After the analysis, reporting was done either using coefficients or marginal effects from the Multivariate Model and the Probit model, following (Cappellari and Jenkins, 2003).

Since GAPs adoption is not randomly assigned, standard probit estimates might be biased due to endogeneity and selection effects. Two key risks in this study are: (i) self-selection into training or exporter contracts, as more commercial or resource-rich farmers are more likely to be targeted or to choose these options; and (ii) omitted variables or reverse causality, where unobserved factors like managerial ability, motivation, or risk attitudes affect both access to support and adoption choices. If these issues are not addressed, they violate the probit exogeneity assumption and lead to inconsistent estimates (Murteira and Ramalho, 2016). To tackle this issue, the study implemented a layered approach. Initially, the probit models to incorporate a comprehensive set of controls, including household demographics, assets and wealth proxies, extension access, group membership, distance to market or packhouse, and fixed effects for agro-ecological zones or wards, to minimise observable confounding. Nonetheless, controls alone cannot eliminate bias due to unobservable factors, so the analysis would explicitly test for endogeneity and adjust accordingly using an Instrumental-Variable Probit or a Control-Function method. Control-function techniques for binary response models, such as probit (Wooldridge, 2015), have become a standard econometric practice for obtaining consistent estimates with endogenous regressors (Qasim *et al.,* 2023).

Under this framework, potentially endogenous variables (especially *training exposure* and *exporter contracts*) are first modelled as functions of valid instruments, factors that shift access to training/contracts but do not directly affect adoption other than through those channels. The resulting first-stage residuals are then included in the adoption probit; a significant residual term indicates endogeneity, while corrected coefficients provide consistent effects (Evdokimov *et al.,* 2024). Because data are gathered through multi-stage clustering, standard errors were adjusted to be cluster-robust at the ward or village level to prevent overstating statistical significance. These procedures collectively ensure that the estimated effects of farm size, training, and exporter contracts on GAPs adoption are not influenced by endogenous placement or farmer self-selection but instead represent more credible causal links (Gabriëlle and Jongmans, 2021; Lewis and Julious, 2021).

The choice of an MVP rather than three separate univariate probit models rests on the conceptual argument that the three GAPs adoption decisions, pre-harvest (e.g., sanitation, IPM, pest control), harvest (use of clean tools, hand-picking, padded harvesting equipment), and post-harvest (produce washing, sorting, grading, compliance with pesticide withdrawal periods), are not independent choices made in isolation, but are likely to be jointly determined by a common underlying factor: the farmer's overall orientation toward, and capacity for, standards compliance. A farmer who is diligent, well-informed, and resource-endowed enough to consistently implement pre-harvest sanitation and IPM practices is also more likely to apply the same diligence to harvest handling and post-harvest grading, not because adopting one practice mechanically causes the adoption of another, but because both decisions are driven by shared, often unobserved, factors such as managerial ability, risk attitudes, perceived returns to quality, and exposure to buyer standards (Cappellari & Jenkins, 2003; Davis John B. *et al.,* 1998).

This shared-unobservable argument is the conceptual basis for expecting non-zero correlations among the error terms of the three adoption equations (Ω in Equation 3.13) and is distinct from the claim that the practices are technically complementary inputs in a production-function sense. At the same time, the three stages differ in the specific resources and constraints they depend on: pre-harvest practices are knowledge- and labour-intensive (shows training is significantly associated with pre-harvest adoption but not harvest or post-harvest adoption), harvest practices depend on simple, low-cost tools and are plausibly diffused through observation and peer learning, while post-harvest practices depend on infrastructure such as storage and grading facilities that may be entirely absent regardless of a farmer's compliance orientation. This means the practices are expected to be correlated through shared latent farmer characteristics, while still responding differently to the specific explanatory variables (farm size, training, contracts) examined in this study, which is consistent with the differentiated findings reported in (training significant for pre-harvest only; contracts significant for pre-harvest and post-harvest but not harvest). The MVP framework accommodates both possibilities simultaneously: it tests for, rather than assumes, cross-equation correlation (via the significance of ρ in Ω), and if pairwise correlations among the three adoption outcomes are not statistically significant, the study falls back to separate univariate probit models for each stage, as already noted.

3.8.4 Measurement of variables

The selection of variables in Table 3.1 is informed by previous empirical research on the adoption of Good Agricultural Practices (GAPs) and other agricultural innovations. The dependent variable, GAPs adoption, were measured as a binary outcome indicating whether farmers adopted pre-harvest, harvest, and post-harvest practices. Independent variables included socio-economic, institutional, and farm-level characteristics. Farm size is included because larger farms often have greater resources and incentives to adopt GAPs (Muriithi and Kabubo-Mariara, 2022). Education level is considered since higher education improves farmers' ability to access, process, and apply technical information, thereby enhancing adoption (Sadique Rahman, 2022). Experience in avocado farming is hypothesized to have mixed effects, as experience can increase skills, but older farmers may be less open to innovation (Gido *et al.,* 2015). Gender was included because male farmers often have better access to markets and extension services, although the effect is context-specific (Murage *et al.,* 2015; Olumeh *et al.,* 2021).

Income is expected to positively influence adoption, as wealthier households can better afford compliance with GAPs standards (Olounlade *et al.,* 2020). Institutional factors such as training, group membership, access to information, and record-keeping were also considered, as they are associated with improved awareness, capacity, and compliance (Chelang'a *et al.,* 2021, 2023; Kariuki, 2025). Finally, variables such as age, contract participation (Mwambi *et al.,* 2016), and number of avocado trees were included, as younger farmers tend to be more innovative (Taramuel-Taramuel *et al.,* 2023), while contracts and farm scale provide incentives to comply with GAPs requirements (Wainaina *et al.,* 2016).

A methodological limitation concerns the measurement of two key explanatory variables, training and contract farming, both of which are operationalised as binary indicators (Table 3.4). This binary coding captures whether a farmer received GAPs training or holds a formal exporter contract, but not the intensity, duration, content, or quality of these arrangements. For training, the underlying survey data distinguish participation by timeframe (last 6 versus 12 months), provider type (private sector, government, NGO/cooperative), and training topic (SPS compliance, certification compliance, post-harvest management, market access, record-keeping). However, the primary MVP specification uses a single binary "received GAPs training" indicator, consistent with the study's general objective of identifying whether training exposure is associated with adoption, rather than which type, provider, or intensity of training matters most. Similarly, contract farming is measured as a single "has a formal contract with an exporter" dummy, without capturing variation in contract terms such as price premiums, input or credit provision, monitoring intensity, or contract duration, none of which were recorded in the original survey instrument.

This coarse measurement of training and contract farming is a recognised limitation in the wider adoption literature, where binary treatment of these variables has been shown to mask heterogeneity in effects and may understate the true relationship between institutional support and practice adoption. In this study, the use of binary indicators was necessitated by the structure of the secondary dataset rather than by design preference. To partially mitigate this limitation, supplementary descriptive analysis disaggregating training by timeframe and provider type to provide a more nuanced picture alongside the binary MVP estimates, and the implications of this measurement constraint for interpreting the magnitude of the training and contract coefficients are revisited in the discussion of limitations.

Table 3.4: Variables for the MVP Model

Variable	Indicators	Measurement/Scale
Dependent variable		
Pre-harvest GAPs adoption	Sanitation records; elimination of dropped fruit; IPM implementation; pest monitoring; fruit fly/FCM control; quarantine pest monitoring; pesticide use and dosage	Binary (1=Yes, 0=No) per practice; composite pre-harvest adoption score
Harvest GAPs adoption	Use of clean harvesting tools; hand-picking; use of poles with baskets	Binary (1=Yes, 0=No) per practice; composite harvest adoption score
Post-harvest GAPs adoption	Proper storage; washing; use of crates; sorting; waste disposal; compliance with pesticide withdrawal period	Binary (1=Yes, 0=No) per practice; composite post-harvest adoption score
Independent variables — Household characteristics		
Gender	Sex of household head/farm operator	Binary (1=Male, 0=Female)
Education	Highest level attained	Ordinal (0=None to 4=Postgraduate); years also recorded continuously
Age	Age of farmer	Continuous (years)
Farming experience	Years growing avocado	Continuous (years; mean=13.83, range 2-44)
Independent variables — Household resource base		
Income	Gross income from avocado sales	Continuous (KES); log-transformed where appropriate
Record keeping	Farm, harvest, hygiene, pest, input, PPE, sales, training, waste records	Binary (1=Yes, 0=No) per record type; composite index
Independent variables — Institutional characteristics		
Training on GAPs	Training in GAPs, SPS/certification compliance, post-harvest management, market access, record keeping; timeframe (6/12 months); provider type	Binary (1=Yes, 0=No); provider recorded categorically (private/government/NGO-cooperative)
Contract farming	Formal supply agreement with exporter/buyer	Binary (1=Has contract, 0=No contract)
Group membership	Membership in farmer group/cooperative	Binary (1=Member, 0=Not member)
Independent variables — Farm characteristics		
Farm size	Acres under avocado cultivation	Continuous (acres); log-transformed in regression
Number of avocado trees	Total trees on farm	Continuous (count); log-transformed where appropriate

Operationalization of qualitative study variables		
Theme	**Indicative open-ended probe**	**Form of response**
Reasons for (non-)adoption of GAPs	"What are the main reasons you have/have not adopted [practice]?"	Free text, subsequently coded into thematic categories
Perceived barriers to GAPs compliance	"What challenges, if any, do you face in meeting GAPs/SPS requirements?"	Free text, thematically coded (e.g., cost, knowledge, infrastructure)
Experience with training and contracts	"Briefly describe your experience with [training/contract] received from [provider]"	Free text, thematically coded
Suggestions for improving GAPs uptake	"What support would help you adopt more GAP practices?"	Free text, thematically coded into policy-relevant categories

3.9 Diagnostics tests

Several diagnostic checks were conducted to assess the suitability of the data and the validity of the econometric models. These diagnostics serve two distinct purposes that should not be conflated: some relate to the *appropriateness of the dependent variable and model specification* (correlation analysis, multicollinearity, and the test for cross-equation correlation that justifies the MVP over separate probits), while others relate to the *distributional properties of the continuous explanatory variables* used in the descriptive analysis and as regressors.

3.9.1 Correlation analysis; Pearson correlation for the variables

To evaluate the factors influencing farmers' choices of GAPs, the study proposes to use Pearson correlation, which measures the linear relationship between variables. This analysis determined the magnitude and direction of associations between different factors (independent variables) and the uptake of Good Agricultural Practices (GAPs) (dependent variable). The Pearson correlation coefficient was computed to evaluate relationships among continuous variables and between continuous and categorical variables that influence GAPs adoption behavior. The coefficient, represented by r, ranges from -1 to +1, where values approaching +1 denote a strong positive correlation, those nearing -1 indicate a strong negative correlation, and those close to 0 reflect no significant linear association. This assessment was to identify the factors most strongly correlated with the adoption of GAPs among smallholder avocado growers in Kenya.

$$r = \frac{n\sum xy - \sum x \sum y}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

Where: n = number of observations or data points; x and y = individual data values for variables X and Y, respectively;$\sum x$ = total sum of all X values;$\sum y$ = total sum of all Y values;$\sum xy$ = sum of the products of corresponding X and Y values;$\sum x^2$ = sum of the squared X values; and$\sum y^2$ = sum of the squared Y values.

3.9.2 Normality test

Although the probit and multivariate probit estimators do not require the dependent variable or the residuals to be normally distributed (the model instead assumes the latent error terms follow a standard normal distribution by construction, which is a modelling assumption rather than an empirical property to be tested in the data), it remains useful to examine the distributional properties of the continuous explanatory variables (e.g., farm size, age, income, number of trees, farming experience) prior to their inclusion in the model. Several of these variables, such as income and farm size, are commonly right-skewed in smallholder farm-survey data, and severe skewness can affect the stability of maximum-likelihood estimation and the interpretation of marginal effects. Normality of these continuous regressors was therefore assessed using skewness and kurtosis statistics, applying the rule of thumb that values within −1 to +1 indicate approximate normality (Effendi Ewan Mohd Matore & Zamri Khairani, 2020), supplemented by the Shapiro–Wilk test, where a p-value greater than 0.05 indicates that the null hypothesis of normality is not rejected (Hernandez, 2021). Where continuous variables exhibited substantial non-normality, this informed the decision to apply log transformations (log of avocado farm size, as used in Equation 3.12 and Table 4.14) prior to inclusion in the MVP model, rather than serving as a diagnostic of the MVP model itself.

3.9.3 Multicollinearity test

Multicollinearity, as explained by Yeatts *et al.* (2017), refers to a situation in which two or more independent variables in a regression model are highly correlated. When such strong relationships exist among predictors, it becomes challenging to determine the individual effect of each variable on the dependent variable. Moreover, multicollinearity tends to inflate the standard errors of the estimated coefficients, thereby reducing the precision and reliability of the regression outcomes. In this study, multicollinearity was examined using the Variance Inflation Factor (VIF) in STATA (Tay, 2017). According to Daoud (2017), a VIF value of 1 indicates the absence of multicollinearity, while values below 5 suggest the presence of moderate correlation that does not pose a critical concern. However, VIF values greater than 5 are indicative of high multicollinearity, which may necessitate corrective measures in the model.

3.9.4 Heteroskedasticity test

Heteroscedasticity refers to a condition in which the variance of errors is not constant across various levels of the independent variables, leading to unequal variability in the prediction of the dependent variable (Kroc & Zumbo, 2018). This inconsistency can affect the efficiency and reliability of regression estimates. In this study, the Breusch–Pagan test was conducted using STATA to detect the presence of heteroscedasticity in the linear regression model. The test evaluates whether the variance of the error terms is systematically related to the independent variables. According to Zhou *et al.* (2017), if the p-value from the test is less than 0.05 ($p < 0.05$), the null hypothesis of homoscedasticity is rejected, indicating the presence of heteroscedasticity. Conversely, a p-value greater than 0.05 suggests that the assumption of constant variance is not violated.

3.9.5 Intraclass Correlation test

According to Gabriëlle & Jongmans (2021), intraclass correlation refers to the extent to which a variable is correlated with its own past values across successive groups. It is useful in identifying whether error terms in a regression model exhibit serial dependence, which may violate the assumption of independent residuals. In this study, the Intra test was applied to determine the presence or absence of autocorrelation in the regression model (Lewis & Julious, 2021). The test examines whether residuals are independent, with values around 2 indicating no intraclass correlation, whereas values significantly below or above 2 suggest positive or negative intraclass correlation, respectively.

3.10 Ethical considerations

The study adhered to the required ethical standards throughout the data collection process. This included obtaining the necessary research authorization, particularly a permit from the National Commission for Science, Technology and Innovation (NACOSTI), prior to the commencement of data collection. Furthermore, prior, free and informed consent was obtained from the selected managers to ensure their voluntary participation in completing the questionnaires. To safeguard privacy and confidentiality, respondents were instructed not to include their names on the questionnaires. The researcher also assured participants that all information provided would be used solely for academic purposes. Participants were informed of their right to refuse participation or withdraw from the study at any time without any form of penalty. In addition, proper academic integrity was maintained through appropriate citation of all consulted sources to avoid plagiarism. The final study was deposited in the Strathmore University Library, making it publicly accessible for academic reference.

3.11 Chapter summary

This chapter has presented the research methodology employed in the study. It started by outlining the research philosophy and design, which formed the foundation and guided the overall execution of the research. It also described the target population, sample size, and the sampling procedures adopted. Furthermore, the chapter explained the data collection methods, approaches used to ensure research quality, and the techniques applied in data analysis and presentation. It also covered the diagnostic tests conducted and concluded with the ethical considerations observed throughout the study.

CHAPTER FOUR: RESEARCH FINDINGS

4.1 Introduction

This chapter presents the study's findings, organized around four specific objectives. The first describes avocado farmers in Murang'a County and evaluates their compliance with Sanitary and Phytosanitary Standards (SPS). It offers a detailed profile of socio-demographic, institutional, and production attributes, along with an assessment of adherence to key Good Agricultural Practices (GAPs) that support SPS requirements. The second examines how farm size influences the adoption of GAPs during pre-harvest, harvest, and post-harvest stages. The third investigates the influence of training on GAPs adoption, determining whether farmers' training improves compliance. The fourth explores how contracts with exporter companies affect GAPs adoption, analyzing how formal market arrangements influence farmers' ability and willingness to meet export standards. These analyses provide a good understanding of the factors driving and hindering SPS compliance in Kenya's avocado export sector.

4.2 Response rate

A total of 725 questionnaires were administered via KoboToolbox to the sampled avocado farmers; 698 were fully completed and retained after data cleaning, and 27 were incomplete and dropped, yielding a response rate of 96.3% (Table 4.1). A response rate this high for a smallholder farm-household survey is unusually elevated relative to typical rural survey benchmarks, where non-response and partial completion are common due to farmer unavailability, fatigue with lengthy digital instruments, or refusal on sensitive questions (income, certification status). Two explanations are plausible and are flagged here rather than treated as straightforward evidence of data quality. First, the figure may genuinely reflect strong rapport between enumerators and farmers in a commercially integrated, cooperative-linked sub-county such as Kandara, where farmers are accustomed to surveys conducted by exporters and cooperatives. Second, the 96.3% figure describes completion among questionnaires that were started; it does not capture farmers who were approached but declined to participate at all, a non-response margin not reported in the original baseline study and therefore not assessable in this secondary analysis. The response rate should therefore be interpreted as an indicator of low item non-response and instrument usability among farmers who agreed to participate, rather than as direct evidence that the achieved sample is representative of the full target population; representativeness is addressed separately in relation to the sub-county concentration.

Table 4.1: Response Rate

Response Rate	Frequency	Proportion (%)
Completed questionnaires	698	96.3
Non-completed questionnaires	27	3.7
Total	725	100

Source: Researcher (2026)

4.2.1 Pilot study and instrument reliability

Prior to the main survey, the instrument was piloted with 73 avocado farmers from areas outside the sampled sub-counties. Internal consistency of the three GAPs adoption scales, assessed using Cronbach's alpha (Table 3.3), was good for pre-harvest practices ($\alpha = 0.81$, 9 items), acceptable for post-harvest practices ($\alpha = 0.79$, 5 items), and acceptable for harvest practices ($\alpha = 0.74$, 2 items), all exceeding the conventional 0.70 threshold (Nunnally & Bernstein, 1995). The pilot results therefore indicate that the three composite GAPs scales used in the descriptive and econometric analysis had satisfactory internal coherence prior to full deployment, with the harvest scale's slightly lower alpha attributable to its small number of items (2) rather than to poor item correlation. KMO and Bartlett's test results similarly indicated that the pre-harvest and post-harvest constructs were suitable for factor-analytic treatment, while the harvest construct showed only marginal sampling adequacy (KMO = 0.500), a limitation that should be borne in mind when interpreting the harvest GAPs composite and the harvest equation of the MVP model.

4.4 Demographic information

4.4.1 Socio-demographic characteristics of the surveyed avocado farmers in Muranga County

Table 4.2 summarises the socio-demographic and farm-level profile of the 698 surveyed avocado farmers. On average, farmers had 13.83 years of avocado-farming experience (SD = 8.74), cultivated 1.35 acres of avocado (SD = 1.53) out of an average total farm size of 1.85 acres (SD = 2.09), reflecting a smallholder system in which avocado is typically integrated into small, mixed-use plots rather than grown on dedicated commercial blocks. The relatively large standard deviations relative to the means, particularly for total farm size (SD exceeding the mean), indicate substantial heterogeneity in landholding: while most farmers operate very small plots, a minority of relatively larger holdings pulls the distribution to the right, a pattern with direct relevance to the farm-size effects.

Table 4.2: Socio-demographic characteristics of the surveyed avocado farmers in Muranga County

Variable	Mean	Min-Max
Farming experience (years)	13.83 (8.74)	2 to 44
Avocado area (acres)	1.35 (1.53)	0.1 to 10
Farm size (acres)	1.85 (2.09)	0.3 to 17
Variable	**Category**	**Proportion (% Yes)**
Gender	Male	70.92
Education Level	None	13.04
	Primary	32.38
	Secondary	48.85
	Tertiary	3.58
	Postgraduate	2.15
Farm Type	Independent farmer	98.71
	Company Farm	1.29
Business Ownership (n = 9)	Mixed-Gender Owned	11.11
	Female-Owned	22.22
	Male-Owned	66.67
Main Market Outlet	Export	98.85
	Local Market	0.43
	Marketing Agents	0.14
	Processor	0.57
Training (SPS/GAPs)	1=yes	50.29
Group Membership	1=yes	14.76
GlobalGAPs Certification	1=yes	33.67
KEPHIS Registration	1=yes	11.32
Extension Access	1=yes	30.95
GACC Registration (China)	1=yes	13.75
GACC Status (Active)	1=yes	13.75
Sub-County		
Kandara	1=yes	83.24
Murang’a South	1=yes	10.32
Gatanga	1=yes	5.16
Mathioya	1=yes	1
Kangema	1=yes	0.14
Murang’a East	1=yes	0.14

Source: Survey Data (2025)

This profile carries several implications for GAPs adoption. A predominantly male-managed, smallholder population with limited formal education (Table 4.2) is consistent with the broader literature's finding that knowledge-intensive practices, particularly pre-harvest IPM and record-keeping, depend heavily on external information sources such as training and extension. The near-universal orientation toward export markets, combined with comparatively low rates of group membership, KEPHIS registration, and access to extension services (Table 4.2), suggests that farmers are operating under strong market pressure to comply with export standards but with relatively thin institutional support to do so. This mismatch between market expectations and institutional support capacity is a recurring structural theme that helps explain the adoption gaps. The pronounced concentration of respondents in Kandara sub-county (Table 4.2) should be borne in mind when interpreting this profile: it most directly describes farming conditions in a relatively commercially integrated, exporter-linked production zone, and may not fully represent farmers in less commercially active sub-counties of Murang'a County.

4.5 Descriptive Statistics

4.5.1 Descriptive results of the adoption portfolio of the Good Agricultural Practices (GAPs) among surveyed avocado farmers in Muranga County

To assess overall compliance levels while avoiding a practice-by-practice recitation of percentages, individual binary GAPs-adoption indicators (Table 4.3) were aggregated into three composite adoption indices, one for each production stage, computed as the proportion of applicable practices adopted by each farmer (ranging from 0 to 1), and summarised using means and standard deviations (Table 4.3). The pre-harvest index (mean = 0.71) indicates that, on average, farmers complied with roughly seven in ten recommended pre-harvest practices, with a moderate spread (SD = 0.19) suggesting that most farmers cluster around a moderately high compliance level rather than splitting into clearly distinct "high" and "low" adopter groups. This relatively strong average performance is concentrated in pest- and pesticide-related practices (quarantine pest monitoring, approved pesticide use, correct dosage), which are precisely the practices that have been the focus of certification-linked training initiatives in Murang'a, including the GlobalG.A.P. push documented for the county. By contrast, sanitation record-keeping and prompt removal of dropped fruit, both practices that depend on routine administrative discipline rather than a single trained skill, pulled the index down, pointing to a gap between technical pest-management competence (which appears well-diffused) and the administrative habits required for full traceability.

Table 4.3: Good Agricultural Practices Adoption Portfolio among surveyed avocado farmers in Muranga County

Pre-harvest GAPs Adoption index	Proportion (% yes)
Sanitation records maintained (1=yes)	49.43
Prompt elimination of dropped fruits (1=yes)	55.01
IPM program implemented (1=yes)	87.25
Pest monitoring (n = 609) (1=yes)	95.73
Chemical control (n = 609) (1=yes)	0.49
Biological control (n = 609) (1=yes)	6.73
Use of fly traps (n = 609) (1=yes)	28.24
Control of fruit fly & False Codling Moth (1=yes)	88.25
Bi-weekly monitoring of quarantine pests (1=yes)	91.83
Immediate pest control measures applied (1=yes)	89.68
Use of approved pesticides only (1=yes)	91.12
Application of correct pesticide dosage (1=yes)	91.12
Pre-harvest GAPs adoption Index	71.56
Variable	**Proportion (% yes)**
Use of clean harvesting tools (1=yes)	98.57
Harvesting by hand-picking (1=yes)	100
Use of pole with basket for harvesting (1=yes)	2.72
Harvest GAPs Adoption Index	67.6
Variable	**Proportion(% yes)**
Proper storage of produce (1=yes)	18.19
Washing of produce (1=yes)	0.57
Use of crates for handling/transport (1=yes)	87.11
Sorting of produce (1=yes)	81.66
Proper disposal of waste (1=yes)	98.14
Compliance with pesticide withdrawal period (REI/PHI) (1=yes)	90.26
Post-harvest GAPs adoption index	63.56

Source: Survey Data (2025)

Control measures for major quarantine pests such as fruit fly and False Codling Moth were practiced by 88.25% of farmers. Additionally, 91.83% reported biweekly monitoring of quarantine pests, and 89.68% reported immediate pest-control applications. High compliance was also observed in the use of only approved pesticides (91.12%) and in the application of the correct pesticide dosage (91.12%). However, sanitation records were maintained by only 49.43% of farmers, and prompt elimination of dropped fruits was practiced by 55.01%. The use of biological control remained very low at 6.73%, with chemical control almost non-existent (0.49%), and fly traps were used by just 28.24% of those implementing IPM. Harvesting GAPs practices showed near-perfect adherence to recommended standards.

The harvest index (mean = 0.67, SD = 0.18) is lower than might be expected given that two of its three component practices (hand-picking, clean tools) are near-universal. The lower mean is driven almost entirely by the third component, use of poles with baskets, which is uncommon. Because hand-picking and pole-with-basket harvesting are largely substitute techniques rather than complementary ones (a farmer typically uses one or the other depending on tree height and the maturity of the orchard), the low mean on this composite index may overstate the practical adoption gap: it partly reflects a method-choice difference driven by orchard characteristics (tree height, age of trees) rather than a genuine compliance failure. This illustrates a limitation of composite indices applied to practices that are not all additive in the same direction.

All farmers (100%) practiced hand-picking of avocados, while 98.57% used clean harvesting tools. The use of poles with baskets for harvesting was minimal, reported by only 2.72% of respondents. Post-harvest GAPs revealed significant weaknesses, particularly in produce handling and storage. Proper storage of produce was practiced by only 18.19% of farmers, and washing of produce was almost non-existent (0.57%). In contrast, the use of crates for handling and transport was high at 87.11%, sorting of produce stood at 81.66%, and proper disposal of waste was observed by 98.14% of respondents. Compliance with the pesticide withdrawal period (REI/PHI) was also high at 90.26%. While avocado farmers in Murang'a exhibited strong compliance with harvesting techniques and several key preharvest pest management practices, critical gaps persist in field sanitation, biological control, and especially postharvest handling and storage.

These weaknesses could undermine fruit quality and limit access to high-value export markets that demand stringent adherence to food safety and quality standards. The post-harvest index (mean = 0.63, SD = 0.16) is the lowest of the three and, unlike the harvest index, reflects a genuine and structurally significant compliance gap. The index is pulled down primarily by two practices with very low adoption: proper storage of produce and washing of produce. Both of these practices share a common structural feature that distinguishes them from the high-adoption post-harvest practices (crate use, sorting, waste disposal, PHI compliance): they require dedicated infrastructure, cold or shaded storage facilities, and a reliable water source/washing station at or near the farm, rather than simply changes in farmer behaviour or knowledge.

4.5.2 Descriptive results of the record keeping and training on GAPs across surveyed avocado farmers in Muranga County

The record-keeping practices among avocado farmers in Murang'a County were generally low, with varying adoption rates observed across most categories of documentation as reported in Table 4.4. Only 31.23% of the farmers-maintained farm logs, making it the most commonly kept record. This was followed by harvest records at 23.21%, hygiene records at 22.49%, and pest control records at 22.06%. Input records were maintained by 20.2% of respondents, while PPE cleaning records stood at 16.33%. Other operational records such as contract files (13.04%), pruning records (11.46%), and manure application records (10.32%) were kept by even smaller proportions of farmers. Compliance with more specialized or administrative record-keeping was particularly low. Sales records were maintained by only 9.17% of farmers, training records by 8.02%, and waste disposal records by 7.88%.

Table 4.4: Record keeping and training on GAPs across surveyed avocado farmers in Muranga County

Variable	Proportion (% Yes)
Farm logs maintained (1=yes)	31.23
Harvest records maintained (1=yes)	23.21
Hygiene records maintained (1=yes)	22.49
Pest control records maintained (1=yes)	22.06
Input records maintained (1=yes)	20.2
PPE cleaning records maintained (1=yes)	16.33
Contract files maintained (1=yes)	13.04
Pruning records maintained (1=yes)	11.46
Manure application records maintained (1=yes)	10.32
Sales records maintained (1=yes)	9.17
Training records maintained (1=yes)	8.02
Waste disposal records maintained (1=yes)	7.88
Workers' contracts documented (1=yes)	6.88
Delivery records maintained (1=yes)	6.16
Human rights records maintained (1=yes)	2.44
Truck cleaning records maintained (1=yes)	2.44
Safety procedures recorded (1=yes)	2.87
Employee policy records maintained(1=yes)	2.01
Scouting logs maintained (1=yes)	2.01
Water, soil, and manure records maintained (1=yes)	1.86
Wage records maintained (1=yes)	1.43
Composite Record Keeping Index	12.67 (0.14)

Source: Survey Data (2025)

Documentation of workers' contracts was reported by 6.88%, while delivery records stood at 6.16%. Records related to human rights (2.44%), truck cleaning (2.44%), safety procedures (2.87%), employee policies (2.01%), scouting logs (2.01%), water/soil/manure management (1.86%), and wage records (1.43%) were maintained by fewer than 3% of the respondents, indicating serious deficiencies in these areas. The findings reveal poor record-keeping practices among avocado farmers in Murang'a. The majority of farmers do not maintain essential farm, harvest, pest control, or hygiene records, while documentation of labor, safety, and environmental management practices is almost non-existent. This low level of record-keeping poses significant challenges to traceability, food safety compliance, and the ability to meet stringent requirements of export markets, particularly for certifications such as Global-GAPs.

4.5.3 Descriptive results of the training on GAPs and avocado production among surveyed farmers in Muranga County

Training uptake among avocado farmers in Murang'a County remained moderate and narrowly focused as shown in Table 4.5. Nearly half of the respondents (46.85%) had received training in Sanitary and Phytosanitary (SPS) measures and compliance, while training on Good Agricultural Practices (GAPs) was reported by approximately 22% of farmers within both the last 6 months (22.21%) and the last 12 months (21.92%).

Table 4.5: Training on GAPS and avocado farming among farmers in Muranga County

Training Type	Timeframe / Provider	Frequency (Yes)	Proportion (% Yes)
GAPs training (1=yes)	Last 6 months	155	22.21
GAPs training (1=yes)	Last 12 months	153	21.92
Certification compliance (1=yes)	Last 6 months	91	13.04
Certification compliance (1=yes)	Last 12 months	88	12.61
Post-harvest management (1=yes)	Last 6 months	38	5.44
Post-harvest management (1=yes)	Last 12 months	35	5.01
Market access (1=yes)	Last 6 months	34	4.87
Market access (1=yes)	Last 12 months	34	4.87
SPS & Compliance (1=yes)	–	327	46.85
Provider of the training			
Private sector provider (1=yes)	–	199	28.51
Government provider (1=yes)	–	11	1.58
NGO / Cooperative provider (1=yes)	–	8	1.15
Record-keeping training (1=yes)	–	56	8.02

Source: Survey Data (2025)

Training on certification compliance was lower, with 13.04% and 12.61% of farmers trained in the last 6 and 12 months, respectively. Participation in post-harvest management training was minimal (5.44% in the last 6 months and 5.01% in the last 12 months), and even fewer farmers received training on market access (4.87% in both timeframes). Record-keeping training was undertaken by only 8.02% of respondents. In terms of training providers, the private sector played the dominant role, delivering training to 28.51% of farmers, compared to only 1.58% by government providers and 1.15% by NGOs or cooperatives. This limited and uneven access to training, particularly in critical areas such as post-harvest management, record-keeping, and market access, suggests considerable capacity gaps that may hinder farmers' ability to consistently meet export quality standards and improve farm management practices.

4.5.4 Descriptive results of the avocado production trends

The study surveyed 698 smallholder avocado farmers in Murang'a County, Kenya in Table 4.6. Results indicate a strong improvement in productivity during this season compared to the previous one. The average total harvest increased from 4,493.52 kg to 5,801.24 kg per farmer, representing a rise of approximately 29%, while the mean yield per tree rose from 134.76 kg to 178.44 kg, an increase of about 32%. Quality indicators also improved modestly, with the average loss rate declining from 5.7% to 4.2% and the proportion of Grade 1 fruit increasing from 88.9% to 90.65%. The export share remained very high at around 88–90%, confirming that the majority of the avocados produced are destined for international markets.

Table 4.6: Descriptive Statistics of Production, Loss, and Income Variables

Production variable (n)	Mean	SD	Min	Median	Max
Total harvest (Last season) n=698	4,493.52	10,947.32	1.5	1,440	120,000
Total harvest (This season) n=698	5,801.24	13,788.67	4	1,580	108,375
Yield per tree (Last season) n=698	134.76	609.04	0.05	75.63	12,155
Yield per tree (This season) n=698	178.44	790.99	0.17	85.71	14,250
Loss rate (Last season) n=689	0.057	0.114	0	0.013	1
Loss rate (This season) n=691	0.042	0.095	0	0.012	1
Export share (Last season) n=695	0.882	0.166	0	0.93	0.99
Export share (This season) n=695	0.898	0.162	0	0.93	0.99
Grade 1 (%) (Last season) n=695	88.9	14.46	0	93	99
Grade 1 (%) (This season) n=695	90.65	13.43	0	93	99
Income (Last season) (KES) n=698	308,958.40	653,017.80	60	105,000	7,225,000
Income (This season) (KES) n=698	471,437.10	1,156,770.00	95	137,370	9,405,000

Last season= 2023/2024, This season=2024/2025
Source: Survey Data (2025)

The average household income from avocado farming rose significantly from KES 308,958 to KES 471,437 per farmer, reflecting an increase of roughly 53%. Despite these positive developments, the data reveals substantial variability and skewness in the distribution, with median harvest levels remaining much lower than the means (around 1,440–1,580 kg), indicating that a relatively small number of larger or more productive farmers continue to pull up the overall averages, while many smallholders operate at more modest production scales.

4.6 Diagnostic tests

4.6.1 Hosmer Lemeshow test

The Hosmer–Lemeshow test was used to assess the goodness-of-fit of the probit models in Table 4.7. The null hypothesis states that there is no significant difference between observed and predicted values, implying a good model fit. For the pre-harvest model (preharvest), the test yielded a p-value of 0.058, which is greater than 0.05. This indicates that we fail to reject the null hypothesis is rejected, suggesting that the model fit the data well. The harvest model (harvest) produced a p-value of 0.1833, which exceeds 0.05. Therefore, the null hypothesis is not rejected, indicating that the model fits the data adequately. For the post-harvest model (postharvest), the p-value of 0.0514 is slightly above the 0.05 threshold. This suggests a borderline but acceptable model fit, implying that the model approximates the observed data.

Table 4.7: Normality Test

Model (Dependent Variable)	Observations	Groups	HL χ^2 (df)	p-value	Model Fit Interpretation
Pre-harvest GAPs adoption (y1_preharvest)	698	10	20.77 (8)	0.0581	Acceptable fit (borderline)
Harvest GAPs adoption (y2_harvest)	683	10	11.34 (8)	0.1833	Good fit (fail to reject H_0)
Post-harvest GAPs adoption (y3_postharvest)	698	10	15.43 (8)	0.0514	Acceptable fit (borderline)

Source: Survey Data (2025)4.6.1 Normality test

The skewness–kurtosis test results indicate that all continuous variables have p-values less than 0.05, leading to the rejection of the null hypothesis of normality. This implies that the variables are not normally distributed. However, this does not pose a serious problem for the analysis since probit and MVP models do not require the independent variables to be normally distributed.

Table 4.8: Normality Test

Variable	Observations	Adj χ^2 (2)	p-value	Normality
Farming experience	698	114.58	0	Not normal
Education level	698	92.59	0	Not normal
Log avocado area	698	11.42	0.0033	Not normal
Number of trees	698	591.82	0	Not normal
Biodiversity (agroforestry)	698	97.8	0	Not normal

Source: Survey Data (2025)

4.6.3 Multicollinearity test

The results indicate that the mean VIF is 2.14, which is well below the commonly accepted threshold of 5. This suggests that multicollinearity is not a serious concern in the model. Although having a contract (VIF = 5.58) slightly exceeds the threshold of 5, it is not high enough to indicate severe multicollinearity. Additionally, all tolerance values are above 0.1, further confirming the absence of problematic collinearity among the independent variables. Therefore, the variables can be retained in the model.

Table 4 9: Multicollinearity test

Variable	VIF	Tolerance (1/VIF)
Has contract	5.58	0.179
Certified GlobalGAPs	4.26	0.235
Sanitation	2.29	0.437
Number of trees	2.26	0.443
Training received	1.89	0.53
Seed licensing	1.86	0.539
Group registration	1.77	0.566
Log avocado area	1.41	0.71
Farming experience	1.1	0.912
Education level	1.1	0.913
Biodiversity (agroforestry)	1.07	0.933
Gender	1.06	0.944
Mean VIF	**2.14**	—

Source: Survey Data (2025)

4.6.4 Heteroskedasticity test

The Breusch–Pagan and White tests were conducted to examine the presence of heteroskedasticity in the models. The null hypothesis for both tests is that the error terms have constant variance (homoskedasticity). For the pre-harvest model, both the Breusch–Pagan test ($\chi^2 = 26.40$, $p < 0.05$) and White's test ($\chi^2 = 167.86$, $p < 0.05$) indicate rejection of the null hypothesis, confirming the presence of heteroskedasticity. Similarly, for the post-harvest model, the Breusch–Pagan test ($\chi^2 = 366.49$, $p < 0.05$) also shows strong evidence of heteroskedasticity. These results imply that the assumption of constant variance is violated. To address this issue, cluster-robust standard errors were applied in the MVP model to correct for heteroskedasticity and within-cluster correlation, thereby ensuring reliable statistical inference.

Table 4.10: Heteroskedasticity test

Model / Test	χ^2 Value	df	p-value	Interpretation
Pre-harvest GAPs (y1_preharvest)				
Breusch–Pagan / Cook–Weisberg Test	26.4	1	0	Heteroskedasticity present (reject H_0)
White's Test	167.86	80	0	Heteroskedasticity present (reject H_0)
Post-harvest GAPs (y3_postharvest)				
Breusch–Pagan / Cook–Weisberg Test	366.49	1	0	Heteroskedasticity present (reject H_0)

Source: Survey Data (2025)

4.6.5 Intraclass Correlation test

The Intraclass Correlation Coefficient (ICC) was used to assess the degree of within-ward clustering in the data. The results indicate that all ICC values exceed the threshold of 0.05, confirming the presence of meaningful clustering effects. Specifically, the GAPs index exhibits a high ICC (0.644), suggesting strong similarity among observations within the same ward. The post-harvest GAPs model also shows substantial clustering (ICC = 0.531), while the pre-harvest model demonstrates moderate clustering (ICC = 0.255). These findings imply that observations within wards are not independent, thereby violating the assumption of independent errors. Consequently, the use of cluster-robust standard errors is justified to correct for within-ward correlation and ensure reliable statistical inference.

Table 4.11: Intraclass Correlation test

Variable / Model	ICC	Std. Error	95% Confidence Interval	Interpretation
Pre-harvest GAPs (y1_preharvest)	0.255	0.078	[0.133, 0.433]	Moderate clustering
Harvest GAPs (y2 harvest)	0.644	0.069	[0.501, 0.765]	Strong clustering
Post-harvest GAPs (y3_postharvest)	0.531	0.086	[0.366, 0.690]	Strong clustering

Source: Survey Data (2025)

Taken together, the diagnostic results in this section have direct implications for how the MVP coefficients in Table 4.14 should be read, and these implications are carried forward rather than treated as a standalone technical exercise. The Hosmer-Lemeshow results (Table 4.7) indicate borderline-to-acceptable fit for the pre-harvest ($p = 0.058$) and post-harvest ($p = 0.051$) equations and good fit for harvest ($p = 0.183$); the borderline p-values for two of the three equations mean that some caution is warranted in over-interpreting small coefficient differences within those equations, though they do not invalidate the overall model (LR $\chi^2(40) = 700.11$, $p < 0.001$. The heteroskedasticity tests (Table 4.10) confirmed significant heteroskedasticity in the pre-harvest and post-harvest equations, and the intraclass correlation results (Table 4.11) confirmed substantial within-ward clustering, particularly for harvest (ICC = 0.644) and post-harvest (ICC = 0.531) adoption. Both findings motivated the use of cluster-robust standard errors at the ward level in the MVP estimation reported in Table 4.14; without this correction, the standard errors on key variables such as training, contracts, and certification would likely be understated, inflating apparent statistical significance. The reported significance levels in Table 4.14 should therefore be understood as already reflecting this correction, rather than as raw, potentially overstated significance levels. The high ICC for harvest adoption (0.644) is also substantively informative in its own right: it indicates that harvest-stage GAPs adoption is more a feature of *where* a farmer is located (ward-level factors such as local cooperative norms, proximity to collection points, or terrain) than of individual farmer characteristics, which is consistent with the near-ceiling adoption levels and limited individual-level coefficient significance found for the harvest equation. The multicollinearity results (Table 4.9), with a mean VIF of 2.14 and only the contract variable approaching the conventional threshold (VIF = 5.58), indicate that the moderate correlation between contract status and certification ($r = 0.717$, Table 4.13) does not materially compromise the precision of either coefficient, though the two variables should not be interpreted as fully independent institutional channels

4.7 Inferential statistics

The inferential statistics produced included correlation and regression analysis results, which were used to examine the relationship between the dependent and independent variables.

4.7.1 Correlation results of the dependent variables

The analysis of the error correlation coefficients in the Multivariate Probit model reveals varying degrees of interdependence among the three stages of Good Agricultural Practices adoption, as shown in Table 4.12. There is a statistically significant positive correlation between pre-harvest and harvest practices ($\rho_{12} = 0.537$, $p < 0.10$), suggesting that unobserved factors influencing pre-harvest adoption have only a carryover effect on harvest practices.

Table 4.12: Pairwise correlation for independent variables

Variable	Pre-harvest Practices	Harvest Practices	Post-harvest Practices
Pre-harvest Practices	1		
Harvest Practices	0.086**	1	
	-0.023		
Post-harvest Practices	0.018	0.262***	1
	-0.63	0	

Source: Survey Data (2025)

A stronger and more statistically significant positive correlation is observed between harvest and post-harvest practices ($\rho_{23} = 0.489$, $p < 0.05$). This suggests that inefficiencies or management issues during harvest are more likely to affect the decisions on post-harvest adoption. The harvest-to-post-harvest transition, therefore, plays a crucial role in the adoption process. Conversely, the link between pre-harvest and post-harvest practices is minimal and not statistically significant ($\rho_{13} = 0.001$, $p > 0.10$), indicating that decisions at these stages are independent and influenced by multiple factors. These differing correlation patterns support the use of the multivariate probit model and highlight the need for targeted interventions at each stage, especially during harvest, which may serve as a bridge between pre- and post-harvest practices.

4.7.2 Correlation results of the independent variables

The correlation analysis indicates that most relationships among the independent variables are weak to moderate. The highest correlation is observed between contract participation and certification ($r = 0.717$, $p < 0.05$), slightly exceeding the commonly accepted threshold of 0.7. Other notable correlations include training and sanitation ($r = 0.651$), and number of trees and farm size ($r = 0.575$). Despite these associations, most correlation coefficients remain below 0.7, suggesting that multicollinearity is not a major concern.

Table 4.13: Results From The Pairwise Correlation of Independent Variables

Variable	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12
(1) Training	1											
(2) Contract	0.554*	1										
(3) Group Reg.	0.111*	0.419*	1									
(4) Certification	0.425*	0.717*	0.199*	1								
(5) Gender	0.096*	0.088*	0.071	0.049	1							
(6) Farming Exp.	-0.118*	-0.078*	-0.079*	-0.090*	-0.001	1						
(7) Education	0.156*	0.094*	-0.02	0.084*	0.064	-0.202*	1					
(8) Ln Avocado Area	0.164*	0.116*	-0.082*	-0.099*	0.182*	0.065	0.051	1				
(9) Sanitation	0.651*	0.593*	-0.032	0.484*	0.097*	-0.115*	0.155*	0.071	1			
(10) No. of Trees	0.229*	0.171*	-0.079*	-0.043	0.108*	-0.007	0.117*	0.575*	0.210*	1		
(11) Biodiversity	-0.045	0.122*	0.029	0.049	-0.025	0.123*	-0.082*	0.082*	0.058	0.088*	1	
(12) Seed Licensing	0.099*	0.090*	0.05	0.083*	0.073	-0.085*	0.067	0.232*	0.012	0.529*	0.012	1

Source: Survey Data (2025)

4.8 Multi-variate Probit (MVP) regression results

The MVP model performs well and is statistically significant (LR $\chi^2(40) = 700.11$, $p = 0.000$), with 698 observations and a log-likelihood of -376.329. These findings highlight the critical role of extension services, certification, and biodiversity conservation in enhancing the integrated adoption of GAPs among avocado farmers. The Multivariate Probit regression results indicate that the adoption of Good Agricultural Practices (GAPs) across pre-harvest, harvest, and post-harvest stages in avocado production is significantly influenced by several institutional, certification, and farm-level factors. In the pre-harvest practices equation, private extension services, contract farming, group registration, GlobalGAP certification, sanitation record keeping, and use of licensed nursery seeds are all positive and highly statistically significant at the 1% level, while training received is positive and significant at the 5% level, and log avocado farm size shows a positive effect significant at the 10% level. For harvest practices, agroforestry biodiversity is positive and highly significant at the 1% level, private extension and GlobalGAP certification are positive and significant at the 10%

level, and the number of trees has a small positive effect significant at the 10% level. In the post-harvest practices equation, agroforestry biodiversity is positive and highly significant at the 1% level, private extension is positive and highly significant at the 1% level, contract farming and GlobalGAP certification are positive and significant at the 5% level. Importantly, the error correlation terms confirm the interdependence of these adoption decisions: the correlation between pre-harvest and harvest practices is positive and significant at the 10% level (ρ_{12} = 0.537), and between harvest and post-harvest practices is positive and statistically significant at the 5% level (ρ_{23} = 0.489), while the correlation between pre-harvest and post-harvest is negligible and insignificant (ρ_{13} = 0.001). These significant positive correlations justify using the multivariate probit model rather than separate univariate probits, as they indicate the presence of unobserved factors that jointly influence adoption decisions across stages.

Table 4.14: MVP results for factors influencing GAPs Adoption

	Pre-harvest Practices	**Harvest Practices**	**Post-harvest Practices**
Variable	**Coef. (Std. Err.)**	**Coef. (Std. Err.)**	**Coef. (Std. Err.)**
Training received	0.514** (0.215)	0.019 (0.456)	0.172 (0.259)
Government extension	0.386 (0.964)	Omitted	-0.392 (0.651)
Private extension	1.173*** (0.227)	0.674* (0.407)	0.955*** (0.236)
Has contract farming	1.505*** (0.268)	-0.717 (0.822)	0.777** (0.333)
Group registered	1.358*** (0.292)	0.375 (0.796)	-0.452 (0.343)
GlobalGAP certification	1.654*** (0.228)	1.289* (0.736)	0.650** (0.315)
Gender (Male=1)	-0.086 (0.154)	-0.726 (0.522)	-0.040 (0.195)
Farming experience (years)	0.004 (0.008)	0.018 (0.023)	0.017 (0.011)
Education level	-0.093 (0.074)	0.102 (0.131)	-0.001 (0.077)
Log avocado farm size	-0.186* (0.103)	-0.447 (0.281)	-0.041 (0.124)
Sanitation record keeping	2.721*** (0.227)	0.089 (0.437)	-0.308 (0.245)
Number of trees	0.000 (0.001)	0.018* (0.011)	0.002 (0.001)
Agroforestry biodiversity	0.251 (0.169)	0.916*** (0.347)	1.183*** (0.178)
Use of licensed nursery seeds	2.362*** (0.573)	Omitted	-0.839 (0.585)
Constant	-4.584*** (0.435)	1.400 (0.872)	0.599 (0.447)
Parameter	**Coefficient (Std. Err.)**	**Statistic**	**Value**
ρ_{12} (Pre-harvest & Harvest)	0.537* (0.218)	**Observations**	698
ρ_{13} (Pre-harvest & Post-harvest)	0.001 (0.118)	**Log Likelihood**	-376.329
ρ_{23} (Harvest & Post-harvest)	0.489** (0.183)	**LR χ^2 (40)**	700.11
		Prob > χ^2	0

Source: Survey Data (2025)

4.8.1 To analyse the influence of farm size on the adoption of GAPs among avocado farmers

The MVP results presented in Table 4.14 reveal that avocado farm size, measured as the log of avocado farm size, had a negative and statistically significant influence on pre-harvest GAP adoption ($\beta = -0.186$, $p < 0.10$). This finding suggests that as farm size increases, the likelihood of adopting pre-harvest GAPs decreases. This result is counterintuitive, as larger farms are expected to have greater resource endowments that could facilitate GAP adoption. However, this negative relationship may reflect the management complexity associated with larger farms, where ensuring consistent compliance with pre-harvest standards across a wider land area becomes increasingly difficult. Larger farms may also be managed with hired labour that is less directly supervised, potentially leading to inconsistent application of pre-harvest practices such as pesticide management, soil health monitoring, and irrigation hygiene. For harvest practices, the coefficient for log avocado farm size was negative ($\beta = -0.447$) but did not attain statistical significance, suggesting that farm size does not exert a statistically meaningful effect on the adoption of harvest-stage GAPs. Similarly, the coefficient for post-harvest GAP adoption was negative but negligible and statistically insignificant ($\beta = -0.041$), indicating that farm size plays a minimal role in determining whether farmers adopt post-harvest practices such as proper handling, sorting, grading, and storage hygiene. The results indicate that the influence of farm size on GAP adoption is most pronounced at the pre-harvest stage, where the negative relationship is statistically significant, while its effect diminishes across the harvest and post-harvest stages. These findings suggest that farm size alone is not a reliable predictor of GAP adoption across all production stages, and that other structural and institutional factors may be more influential in shaping farmers' adoption decisions.

4.8.2 To assess the effect of training on GAPs among avocado farmers

The MVP results in Table 4.14 indicate that training received had a positive and statistically significant effect on the adoption of pre-harvest GAPs ($\beta = 0.514$, $p < 0.05$). This finding confirms that farmers who received training on GAPs were significantly more likely to adopt pre-harvest practices compared to those who did not receive training. Pre-harvest practices, which include activities such as soil preparation, input use, pest and disease management, and irrigation management, require a strong knowledge base. Training equips farmers with the technical knowledge necessary to implement these practices correctly and consistently, which explains the significant positive association observed at this stage.

For harvest GAPs adoption, the coefficient for training received was positive (β = 0.019) but was not statistically significant, suggesting that training does not differentiate harvest practice adoption between trained and untrained farmers. This could be attributed to the fact that harvest practices such as careful picking, use of clean containers, and avoiding physical damage to fruit are observable and may be learned through social learning or imitation from peers and market intermediaries, thereby reducing the exclusive role of formal training at this stage. Similarly, the coefficient for training received on post-harvest GAPs adoption was positive (β = 0.172) but did not attain statistical significance. Post-harvest practices including cooling, sorting, grading, and hygienic transportation require specialised infrastructure and facilities that training alone may not overcome. Even well-trained farmers may be constrained by limited access to cold storage, appropriate packaging materials, and post-harvest handling equipment, which could explain why training does not significantly translate into improved post-harvest GAPs adoption. Taken together, the results underscore the critical role of training in promoting pre-harvest GAPs adoption, while suggesting that at the harvest and post-harvest stages, other complementary factors beyond training, such as infrastructure, market linkages, and institutional support, may be equally or more important. These findings point to the need for targeted training programmes that are accompanied by practical support mechanisms to ensure adoption across all stages of the production chain.

4.8.3 To assess the influence of contracts with exporter companies on GAPs adoption

The MVP results in Table 4.14 show that contract farming had a positive and statistically significant effect on both pre-harvest and post-harvest GAPs adoption. Specifically, the coefficient for pre-harvest GAPs adoption was positive and highly significant (β = 1.505, $p < 0.01$), indicating that farmers with formal contracts with exporter companies were more likely to adopt pre-harvest GAPs compared to their non-contracted counterparts. The coefficient for post-harvest GAPs adoption was also positive and statistically significant (β = 0.777, $p < 0.05$), confirming that contract farming similarly promotes the uptake of post-harvest GAPs such as proper handling, sanitation, and traceability practices. These results are consistent with the role that export contracts play in creating strong market incentives and compliance requirements that drive GAPs adoption. Export contracts typically come with clearly defined quality and safety standards that farmers must meet to fulfil their contractual obligations. In the context of avocado production, exporters often require contracted farmers to adhere to specific pre-harvest protocols, including regulated pesticide use, proper irrigation practices, and record-keeping, as conditions of delivery acceptance.

Similarly, post-harvest requirements such as appropriate sorting, grading, packaging, and hygienic storage are commonly embedded in contract terms to meet international market standards. Farmers who enter into such arrangements therefore face direct and binding incentives to adopt GAPs across these stages, which explains the significant positive associations observed. In contrast, the coefficient for harvest GAPs adoption under contract farming was negative and statistically insignificant ($\beta = -0.717$). This finding suggests that contract farming does not have a statistically meaningful influence on harvest-stage GAPs adoption. One explanation is that harvest practices, which involve the actual picking and immediate handling of the fruit in the field, are less directly monitored by exporters under contract arrangements. While pre-harvest and post-harvest stages are more easily documented and inspected through farm records and delivery assessments respectively, harvest-stage compliance may be more difficult for exporters to enforce and verify, thereby weakening the contractual incentive at this stage. The results strongly support the role of contract farming as a key institutional mechanism for promoting GAPs adoption, particularly at the pre-harvest and post-harvest stages. The findings highlight that formal market linkages through export contracts serve not only as economic arrangements but also as vehicles for technology transfer and standards compliance, enabling farmers to meet the rigorous food safety and quality requirements of international avocado markets.

4.9 Cross-adoption of GAP practices across production stages

The results in Table 4.15 indicate differing patterns of association between GAPs adoption across production stages. There was no statistically significant relationship between pre-harvest and post-harvest GAPs adoption ($\chi^2 = 0.232$, $p = 0.630$), with similarly high proportions of post-harvest adoption among both pre-harvest non-adopters (90.79%) and adopters (91.82%). In contrast, a strong and statistically significant association was found between harvest and post-harvest GAPs adoption ($\chi^2 = 47.739$, $p < 0.001$). Farmers who adopted harvest GAPs were more likely to adopt post-harvest practices (92.15%) than those who did not (30.00%). These findings suggest that adoption continuity is more pronounced between harvest and post-harvest stages than between pre-harvest and post-harvest stages. This finding validates the choice of the multivariate probit specification over separate univariate probits and is consistent with the theoretical expectation, implicit in the behavioural adoption literature, that farmers approach compliance as a portfolio of interrelated decisions rather than a series of isolated binary choices. The non-significant correlation between pre-harvest and post-harvest adoption, however, suggests that the sequential interdependence is localized to adjacent value chain stages, a nuance that prior single-equation adoption studies which dominate the Kenyan horticulture literature, are structurally unable to detect.

Table 4.15: Cross-adoption of GAP Practices Across Production Stages

GAP Stage Comparison	Category	Post-harvest GAP: No	Post-harvest GAP: Yes	Total
Pre-harvest vs Post-harvest	No	35 (9.21)	345 (90.79)	380
	Yes	26 (8.18)	292 (91.82)	318
	Total	61 (8.74)	637 (91.26)	698
	χ^2 (p-value)	0.232 (0.630)}		
	Fisher's exact	[3] [0.687]		
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Harvest vs Post-harvest	No	7 (70.00)	3 (30.00)	10
	Yes	54 (7.85)	634 (92.15)	688
	Total	61 (8.74)	637 (91.26)	698
	χ^2 (p-value)	47.739 (0.000)		
	Fisher's exact	[3] [0.000]		

Source: Survey Data (2025)

4.10 Mean differences in farmer and farm characteristics by GAPs adoption stage

The results reveal notable differences in farmer and farm characteristics across GAPs adoption stages. For pre-harvest GAPs, adopters had significantly less farming experience (12.73 years) than non-adopters (14.75 years; $p = 0.002$) and also operated smaller avocado areas (1.18 vs. 1.48 acres; $p = 0.011$). However, there were no significant differences in total farm size or number of trees. In the case of harvest GAPs, adopters exhibited significantly greater farming experience (13.91 vs. 8.40 years; $p = 0.025$) and managed more trees (56.67 vs. 27.60; $p < 0.001$) than non-adopters. Differences in farm size and avocado area were not statistically significant. Similarly, for post-harvest GAPs, adopters had significantly greater farming experience (14.21 vs. 9.87 years; $p < 0.001$), suggesting that experience plays a key role at this stage. However, differences in farm size, avocado area, and number of trees were not statistically significant. These findings indicate that while farming experience consistently influences GAPs adoption, particularly at harvest and post-harvest stages, farm scale indicators show limited and inconsistent effects.

Table 4.16: Mean Differences in Farmer and Farm Characteristics by GAPs Adoption Stage

Variable	Pre-harvest GAPs (No) Mean (SD)	Pre-harvest GAPs (Yes) Mean (SD)	Diff	p-value
Farming experience (years)	14.75 (8.57)	12.73 (8.83)	2.01	0.002**
Farm size (acres)	1.93 (1.83)	1.75 (2.36)	0.18	0.274
Avocado area (acres)	1.48 (1.46)	1.18 (1.60)	0.3	0.011**
Number of trees	55.30 (108.89)	57.40 (165.44)	-2.09	0.847
Variable	**Harvest GAPs (No) Mean (SD)**	**Harvest GAPs (Yes) Mean (SD)**	**Diff**	**p-value**
Farming experience (years)	8.40 (6.45)	13.91 (8.75)	-5.51	0.025**
Farm size (acres)	1.79 (0.86)	1.85 (2.10)	-0.06	0.846
Avocado area (acres)	1.19 (0.74)	1.35 (1.54)	-0.16	0.528
Number of trees	27.60 (12.26)	56.67 (138.41)	-29.1	0.000***
Variable	**Post-harvest GAPs (No) Mean (SD)**	**Post-harvest GAPs (Yes) Mean (SD)**	**Diff**	**p-value**
Farming experience (years)	9.87 (8.29)	14.21 (8.69)	-4.34	0.000***
Farm size (acres)	1.63 (1.63)	1.87 (2.13)	-0.24	0.298
Avocado area (acres)	1.15 (1.22)	1.36 (1.56)	-0.21	0.213
Number of trees	43.85 (48.71)	57.44 (143.07)	-13.6	0.109

Source: Survey Data (2025)

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4.11 Distribution of GAPs score

The distribution of GAPs scores indicates that most farmers cluster around moderate to high adoption levels, particularly for pre-harvest practices where scores of 9 and 11 dominate. Harvest GAPs adoption is nearly universal, with the vast majority of farmers attaining the maximum score. Similarly, post-harvest practices show a strong concentration at higher scores (3 and 4), suggesting widespread uptake of recommended practices across later stages of production.

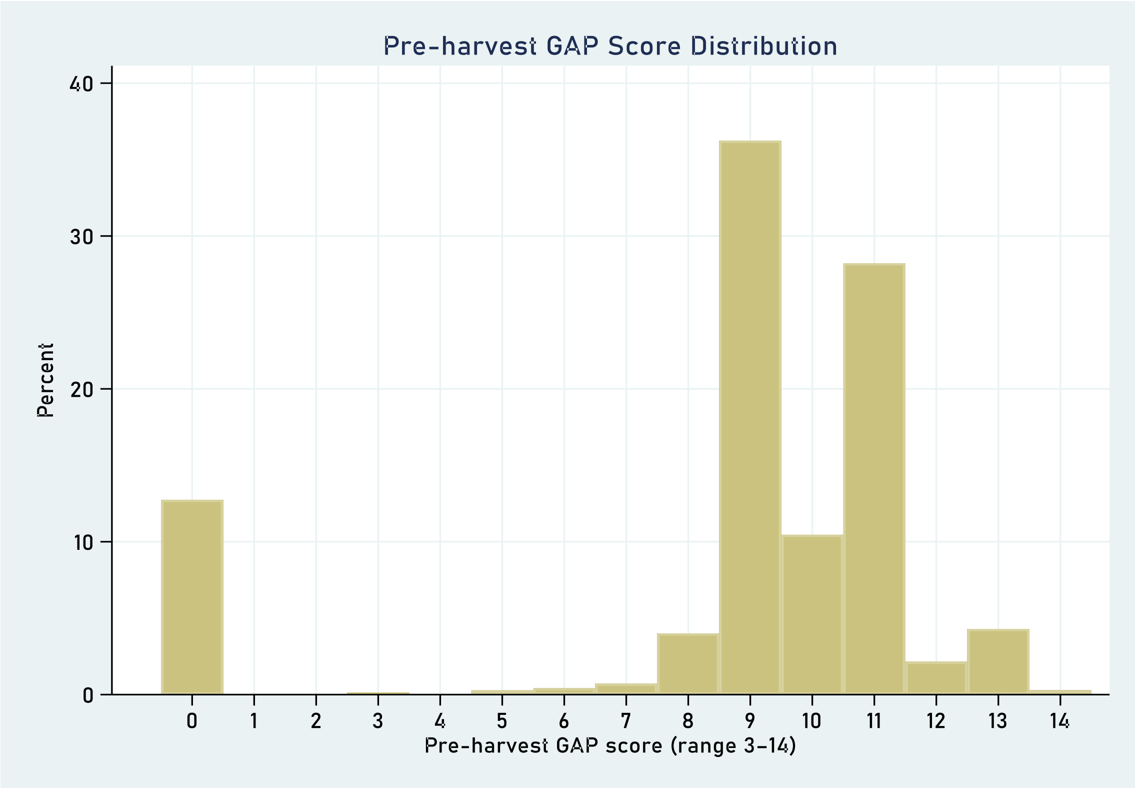

Figure 4.1: Preharvest GAPs score distribution

Source: Survey Data (2025)

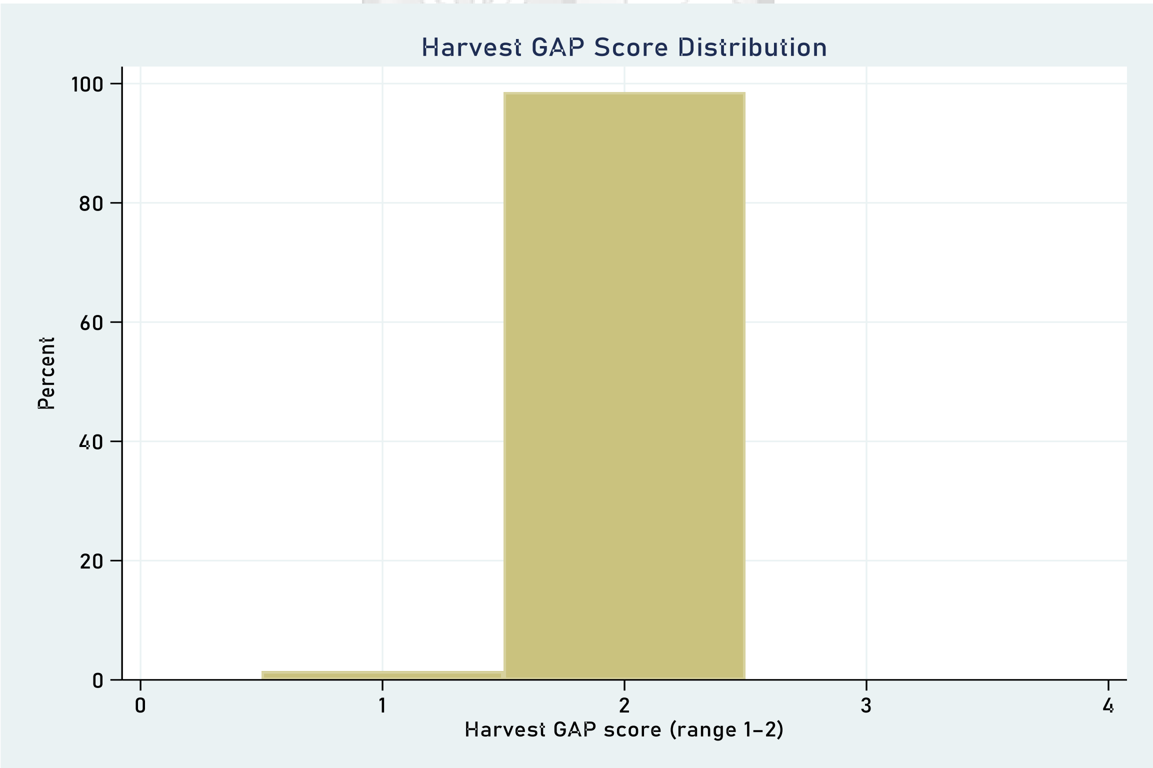

Figure 4.2: Harvest GAPs score distribution

Source: Survey Data (2025)

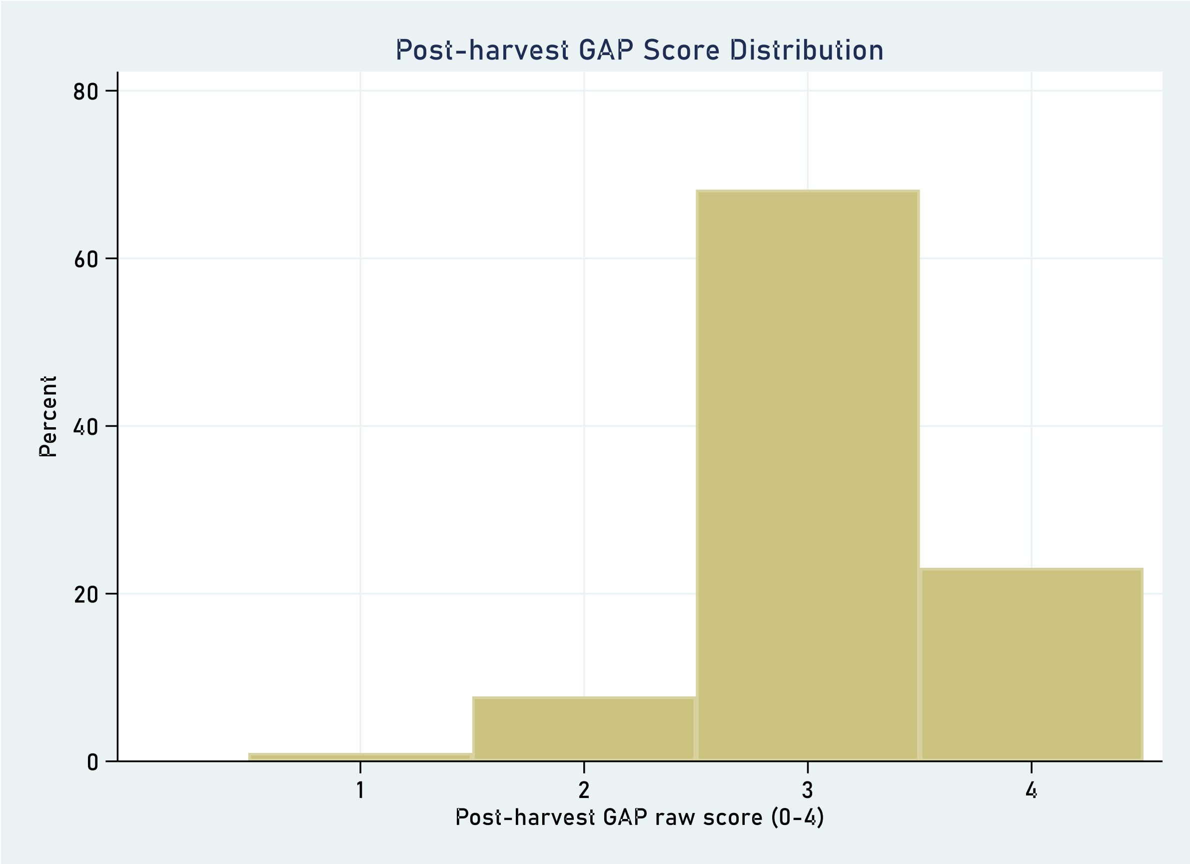

Figure 4.3: Post-harvest GAPs score distribution

Source: Survey Data (2025)

4.12 Mean differences using t-test for production outcomes

Of the 698 avocado farmers surveyed, 537 (76.93%) were classified as high GAPs adopters, while 161 (23.07%) were low GAPs adopters. Nearly all farmers (690 out of 698; 98.9%) sold their produce through the export market. Among export-market farmers, 77.1% were high GAPs adopters compared to 22.9% who were low adopters, a pattern consistent with the overall sample distribution. The remaining farmers sold through local markets (n=3), marketing agents (n=1), or processors (n=4), though numbers in these categories were too small to draw meaningful conclusions. The association between market outlet and GAPs adoption status was not statistically significant ($p = 0.051$), though the p-value is borderline and warrants cautious interpretation, particularly given the very uneven distribution across outlet categories. High GAPs adopters outperformed low adopters on all four market performance indicators, though statistically significant differences were only observed for the last season variables (Table 4.17).

Table 4.17: Comparison of Production and Export Performance by GAPs Adoption Status

GAPs Adoption Status	Frequency	Percent (%)		
Low GAP Adopters	161	23.07		
High GAP Adopters	537	76.93		
Total	698	100		
Association Between Main Market Outlet and GAPs Adoption Status				
Main Market Outlet	**Low GAP Adopters n (%)**	**High GAPs Adopters n (%)**	**Total**	**p-value**
Export	158 (22.90)	532 (77.10)	690	
Local Market	2 (66.67)	1 (33.33)	3	
Marketing Agents	1 (100.00)	0 (0.00)	1	
Processor	0 (0.00)	4 (100.00)	4	
Total	**161 (23.07)**	**537 (76.93)**	**698**	**0.051**
Variable	**Low GAPs Adopters Mean (SD)**	**High GAPs Adopters Mean (SD)**	**Mean Difference**	**t-value**
Export share last season	0.849 (0.236)	0.892 (0.138)	-0.044**	-2.224
Export share current season	0.883 (0.229)	0.902 (0.135)	-0.02	-1.04
Grade 1 produce last season (%)	85.40 (22.54)	89.95 (10.75)	-4.55**	-2.469
Grade 1 produce current season (%)	89.42 (20.68)	91.02 (10.29)	-1.6	-0.948

Last season= 2023/2024, This season=2024/2025
Source: Survey Data (2025)

For export share in the last season, high GAPs adopters exported a significantly greater proportion of their harvest (mean = 0.892, SD = 0.138) compared to low adopters (mean = 0.849, SD = 0.236), with a mean difference of −0.044 ($t = -2.224$, $p = 0.027$). Similarly, Grade 1 production in the last season was significantly higher among high GAPs adopters (mean = 89.95%, SD = 10.75%) than low adopters (mean = 85.40%, SD = 22.54%), a difference of 4.55 percentage points ($t = -2.469$, $p = 0.015$). In contrast, differences in the current season were in the same direction but did not reach statistical significance, export share (mean difference = −0.020, $t = -1.040$, $p = 0.300$) and Grade 1 produce (mean difference = −1.60 percentage points, $t = -0.948$, $p = 0.345$). The narrowing of standard deviations among low adopters between seasons (export share SD declining from 0.236 to 0.229; Grade 1 SD from 22.54 to 20.68) may suggest some convergence in performance over time, though the high adopter group consistently maintained tighter, more uniform performance. The results suggest that higher GAPs adoption is associated with better and more consistent export performance, particularly in produce quality and export share, with the strongest evidence in the previous season's data.

4.13 Chapter summary

This chapter presents the findings derived from the completed and returned questionnaires. The results cover the response rate, respondents' demographic characteristics, descriptive statistics, diagnostic test outcomes, and the results of correlation and regression analyses.

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CHAPTER FIVE: DISCUSSION, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter discusses the findings presented in Chapter Four in relation to existing literature and theoretical frameworks. The discussion is organised around the study's key thematic areas, namely: the socio-demographic profile of avocado farmers; GAPs adoption patterns; record-keeping and training practices; production trends; and the factors influencing GAPs adoption across the pre-harvest, harvest, and post-harvest stages.

5.2 Response rate

The response rate attained in this study exceeds the 70% threshold widely recommended as sufficient for reliable statistical inference in agricultural survey research Mugenda & Mugenda (2019) recommend that a response rate of 70% and above is sufficient for statistical analysis. In this case, the attained response rate exceeds the recommended threshold, indicating strong participation from the respondents. This level of engagement enhances the reliability of the findings and suggests that the results are representative of the target population. Consequently, it also improves the credibility and generalizability of the study outcomes (Taherdoost & Madanchian, 2024). The use of Kobo Collect for digital data collection is consistent with evidence that technology-assisted survey administration reduces non-response and minimises data entry errors in smallholder agricultural surveys (Ballivian *et al.,* 2015). The high response rate strengthens the credibility and generalisability of the findings to the broader population of avocado farmers in Murang'a County. The 96.3% completion rate among administered questionnaires (Table 4.1) reflects low item non-response and suggests the instrument was usable and well-received among farmers who agreed to participate. However, this figure should not, on its own, be taken as evidence that the achieved sample is representative of avocado farmers across Murang'a County. Representativeness depends jointly on (i) the completion rate among those approached, which this study's secondary dataset does not allow assessment, and (ii) the geographic and institutional composition of the sample, which is heavily concentrated in Kandara sub-county (83.24%). The high completion rate is therefore best understood as a data-quality indicator (the dataset contains few partially completed or unusable records) rather than as a generalisability indicator.

5.3 Socio-demographic characteristics of avocado farmers

The sample (n = 698) is predominantly male-managed (mean gender indicator consistent with male majority), with moderate farming experience (mean = 13.83 years, SD = 8.74) and small avocado holdings (mean = 1.35 acres, SD = 1.53, out of a mean total farm size of 1.85 acres, SD = 2.09). The predominance of male farm managers is consistent with documented gender inequalities in land access, input markets, and commercial participation across Sub-Saharan Africa, where restricted land titling and limited credit access constrain women's participation in export-oriented (Fischer & Qaim, 2012; Quisumbing *et al.,* 2014). Rather than simply restating this as confirmatory, it is worth noting what this study's data can and cannot say about the mechanism: the dataset records gender as a binary indicator of the farm operator but does not capture land tenure status, so whether the observed gender skew reflects exclusion from land ownership, from cooperative membership, or from the export-contracting relationships, cannot be distinguished here. Given that gender itself was not a significant predictor in any of the three MVP equations, the demographic profile appears to function more as a description of the population studied than as an explanatory factor in adoption outcomes, a point the original discussion did not make explicit. The small landholding sizes (mean avocado area 1.35 acres, SD 1.53) are consistent with Kenya's well-documented pattern of land fragmentation through inheritance (Jayne *et al.,* 2016), but framing it alone risks treating farm size as background context when farm size is an active, if counterintuitive, predictor of pre-harvest adoption. The demographic profile and the regression results should therefore be read together: the population is one in which essentially all farms are "small" by international standards (max avocado area = 10 acres) so the negative farm-size coefficient describes variation within a smallholder population, not a comparison between smallholders and large commercial operations. The near-universal export orientation (mean export-market participation close to 1, Table 4.2), combined with low group membership and extension access, means that the institutional variables (contracts, certification, private extension) are operating against a backdrop where almost all farmers face export-market pressure, but few have institutional support to meet it. This combination, high market exposure, low institutional support, is arguably the central structural feature of this sample, and it reframes the demographic findings not as a list of farmer characteristics but as evidence of an access gap: the demand-side pressure to comply with GAPs (via export orientation) substantially outpaces the supply-side institutional infrastructure (extension, certification bodies, group structures) available to help farmers meet that demand.

5.4 GAPs adoption among avocado farmers

5.4.1 Pre-harvest and farming GAPs

The strong compliance in pest management practices, particularly in integrated pest management implementation and approved pesticide use, is consistent with evidence that market-driven compliance is strongest in areas directly monitored through buyer audits and certification assessments (Asfaw *et al.,* 2010; Graffham *et al.,* 2017). In contrast, the limited adoption of field sanitation records and the prompt removal of dropped fruit reflect the attitude-behaviour gap in the compliance literature, where awareness of recommended practices does not translate into consistent implementation owing to labour constraints and limited supervisory oversight (van den Berg *et al.,* 2021).

Pre-harvest adoption shows comparatively strong, though uneven, compliance. Strong compliance with pest- and pesticide-related practices (correct dosage, quarantine pest monitoring) is consistent with market-driven monitoring by exporters and certification bodies, which has been shown elsewhere to drive uptake of audit-relevant practices. However, sanitation record-keeping and prompt removal of dropped fruit lag considerably behind, and this gap is not simply an "attitude-behaviour" issue. If buyer monitoring genuinely drives compliance with visible, audit-relevant practices, it is notable that this same mechanism does not appear to extend to sanitation records, which are precisely the kind of documentary evidence that certification audits are designed to check. A more critical reading is that buyer monitoring in this context may be selective, focused on outcome-relevant practices (residue levels, visible pest damage) rather than process documentation, meaning the "market discipline" explanation for high pesticide compliance does not automatically extend to the administrative dimensions of compliance.

5.4.2 Harvest GAPs

The near-universal adherence to recommended harvest practices is consistent with evidence that operationally simple and observable practices diffuse more readily through peer learning than technically complex protocols (Kondylis *et al.,* 2017). The low uptake of harvest poles with baskets signals an equipment access gap with downstream implications for produce quality, given that mechanical bruising during picking is a primary driver of grade downgrading in avocado export chains (Singh & Cramer, 2019). Harvest-stage practices show near-saturation adoption for hand-picking and clean-tool use, but very low adoption of pole-with-basket harvesting. A peer-learning diffusion explanation, that simple, visible practices spread easily through observation, is plausible but does not explain why pole-with-basket harvesting failed to diffuse if peer learning is the operative mechanism for this stage. A more defensible interpretation is that pole-with-basket harvesting is not low-adoption because it failed to diffuse, but because it serves a different orchard-management need (harvesting from taller, typically older trees) than hand-picking does. The two practices function as substitutes conditional on tree height and age, rather than as competing innovations at different stages of diffusion. This suggests the harvest-stage adoption measure may partly capture orchard characteristics as much as farmer behaviour.

5.4.3 Post-harvest GAPs

The critical compliance gaps in produce storage and washing represent the most consequential food safety vulnerability identified in this study. The post-harvest stage is widely recognised as the point of greatest deterioration in produce quality and safety risk in tropical fruit export chains under inadequate cold chain infrastructure (Sheahan & Barrett, 2017a). The comparatively higher adoption of sorting, crating, and waste disposal confirms that practices directly evaluated at the buyer grading stage are adopted at higher rates than those whose compliance benefits are less immediately observable (Swinnen & Vandemoortele, 2009). Post-harvest adoption is the weakest of the three stages, driven primarily by low adoption of proper storage and washing of produce, both of which depend on dedicated infrastructure (cold or shaded storage, a reliable water source) rather than simply farmer knowledge or willingness. This pattern is consistent with the low rates of extension access and formal certification observed in the sample, and with the broader literature noting that post-harvest infrastructure is typically provided or co-financed by cooperatives, exporters, or government programmes rather than individual smallholders. Importantly, the low post-harvest index does not appear to primarily reflect a lack of farmer awareness: farmers in the same sample show high compliance with other post-harvest practices that require no capital investment (waste disposal and compliance with pesticide withdrawal periods). The gap is therefore better characterised as a structural infrastructure deficit at the farm and aggregation-point level, rather than a behavioural shortfall, and training data show that post-harvest management training reached only a small fraction of farmers, suggesting that even the institutional channel that could in principle substitute for missing infrastructure (training in low-cost alternatives such as shade-drying or improved crate ventilation) has barely reached this population.

5.5 Record-keeping practices

The pervasive lack of farm documentation poses a fundamental challenge to traceability and audit compliance in the study area. Record-keeping is a cornerstone requirement of both Global-GAPs and the Codex Alimentarius framework, as systematic documentation of inputs and processes is essential for traceability in the event of food safety incidents (FAO & WHO, 2023). The near-absence of labour, safety, and environmental management records is particularly consequential given the escalating scrutiny of social and environmental standards in international agrifood value chains (Reardon *et al.,* 2019). These findings are consistent with evidence that structural barriers, including low functional literacy, insufficient extension support, and limited perceived benefit from documentation, undermine record-keeping behaviour among smallholder export farmers in Sub-Saharan Africa (van den Berg *et al.,* 2021).

Record-keeping practices show a uniformly low adoption rate across the sample. This near-uniform absence is analytically significant beyond its face value: record-keeping is not itself a technical farming practice, but an administrative function underpinning traceability and the documentary evidence required for certification and buyer audits. Its near-absence, including among farmers who hold GlobalG.A.P. certification, points to two possible explanations. Either certification was obtained or maintained with relatively limited documentary rigour, or record-keeping requirements are being fulfilled at an aggregation point (by the cooperative or exporter on farmers' behalf) rather than at farm level. Either interpretation points to a structural vulnerability: if certification audits tighten documentary requirements, or if farm-level traceability becomes necessary (for example, in response to a contamination incident), the current near-absence of farm-level records would constitute a significant compliance risk that is not currently visible in headline certification or export-share statistics. This is a more consequential interpretation than simply concluding that farmers do not keep records, and it has different policy implications: if records are kept centrally, the priority is ensuring the integrity and accessibility of those centralised records, an institutional or audit-system question, rather than farmer training in record-keeping, an individual-capacity question.

5.6 Training on GAPs

The dominance of private-sector training providers reflects the structural transition in agricultural advisory service delivery documented across Sub-Saharan Africa, where public extension systems have weakened and private actors, including exporters and certification bodies, have assumed a growing role in training (K. Davis & Sulaiman V., 2014; Faure *et al.,* 2012). While private-led training effectively transmits commercially relevant compliance knowledge, its content is typically shaped by the specific interests of contracting firms, which can create gaps in broader farm management knowledge. The very low participation in post-harvest management and record-keeping training is particularly significant, as these are the domains in which the most critical compliance deficits were identified, suggesting that the current training architecture does not adequately address the full spectrum of farmer knowledge needs (Ragasa *et al.,* 2013).

Private-sector actors are the dominant training providers in this sample, with government and NGO/cooperative providers reaching far fewer farmers. This pattern carries more analytical weight than simply reflecting a sector-wide shift toward private advisory services. If private-sector actors, predominantly exporters and input suppliers, are the dominant training providers, their training content is plausibly shaped by what is commercially relevant to them: pesticide use, integrated pest management, and input application directly affect crop quality and yield, and inputs are often supplied by the same actors delivering training, creating a direct commercial incentive to train on pre-harvest practices. Post-harvest handling, storage, and record-keeping primarily affect the exporter's downstream costs (rejection rates, traceability) rather than the input-supplier's commercial interest, and training data show post-harvest management training reaches only a small fraction of farmers.

This is not simply a "training gap" to be closed by more training in general; it may reflect a structural misalignment between who delivers training and what that provider has a commercial incentive to teach. Under this reading, the training gap in post-harvest content is an institutional-incentive problem, not merely a coverage problem, and expanding training without addressing who delivers it and why would be unlikely to close the gap.

A second, under-examined issue is the quality and delivery format of training. A binary "received training (yes/no)" measure confirms that some form of training is associated with higher pre-harvest adoption, but says nothing about whether one-off demonstrations, ongoing farmer-field-school models, or digital extension messages differ in effectiveness. Any recommendation to "expand training" should explicitly address delivery format and content focus, not just reach, since delivery modality is a recognised moderator of training effectiveness in the literature.

5.7 Avocado production trends

The documented improvement in yields, export share, and household income reflects the ongoing commercialisation of avocado farming in Murang'a County, consistent with broader evidence of productivity growth in Kenya's avocado subsector driven by rising global demand and improved agronomic practices (B. W. Muriithi & Matz, 2015; Tschirley *et al.,* 2015). Notwithstanding these positive developments, the substantial divergence between mean and median production levels indicates significant intra-community inequality, with a relatively small number of better-resourced farmers driving population-level averages. This distributional pattern is a widely documented characteristic of smallholder export-crop agriculture and raises important questions about the inclusivity of value chain development (Maertens & Winnen, 2015; Swinnen & Vandemoortele, 2009). The modest reductions in loss rates warrant cautious interpretation, given the post-harvest compliance gaps identified, as these gains may reflect favourable seasonal conditions rather than systemic quality management improvements.

5.8 Drivers of adoption practices

5.8.1 To analyse the influence of farm size on the adoption of GAPs among avocado farmers

The prevailing theoretical expectation in the standards adoption literature is that farm size should be positively and consistently associated with the uptake of compliance-intensive practices such as GlobalG.A.P., owing to the capacity of larger farms to spread fixed compliance costs, including audit fees, record-keeping infrastructure, and post-harvest handling investments, over greater output volumes (Asfaw *et al.,* 2009). Indeed, cost-based analyses of other smallholder export crops document a distinct compliance threshold below which certification becomes financially prohibitive for smallholders, reinforcing the expectation that scale is a key enabler of adoption (Annor *et al.,* 2024). Studies from Kenyan export horticulture chains, particularly those focused on beans and pineapple, similarly report significant scale barriers that disadvantage small producers in global value chains (Chelang'a *et al.,* 2021). However, the findings of the present study challenge the universality of this scale hypothesis, at least in the context of avocado production in Murang'a. The MVP results reveal that log avocado farm size exerts a positive and weakly significant effect exclusively on pre-harvest GAPs adoption, while its effects on harvest and post-harvest adoption are statistically negligible.

More strikingly, the mean comparison analysis indicates that pre-harvest adopters operate on significantly smaller avocado farm areas compared to non-adopters a finding that runs counter to the positive scale hypothesis advanced in much of the prior literature. This suggests that in the Murang'a avocado context, farm size does not function as a consistent or overarching driver of GAP compliance across the value chain. This divergence from the established literature can be interpreted in several ways. First, smaller avocado farmers may face lower internal coordination costs and may be more responsive to extension services and training programs, particularly at the pre-harvest stage, where information-based interventions around pesticide management and integrated pest management (IPM) are most delivered. Second, the finding may reflect selection into export channels: exporters in Murang'a may actively target smaller, more manageable farms for technical support and certification assistance, thereby enabling compliance among farmers who would otherwise be constrained by resource limitations. This interpretation is consistent with the observation by (Gichuki *et al.,* 2020; Lemeilleur, 2013) that wealth and resource endowments shape adoption pathways, but not always in a linear or uniform direction.

It also aligns with the broader critique raised in the literature that most farm size studies treat wealth as a static proxy without sufficiently disaggregating the mechanisms, liquidity, risk capacity, or market access, through which scale influences adoption decisions (Gichuki *et al.,* 2020; Lemeilleur, 2013). Furthermore, the number of trees, an alternative proxy for farm-level scale, was found to be positively and significantly associated with harvest GAP adoption, suggesting that operational scale in harvest activities may matter more for compliance with picking and handling practices than farm area per se. This nuanced finding underscores a point emphasized in the methodological critique of the literature: that scale effects on adoption are stage-specific and sensitive to how scale is operationalized, a weakness acknowledged in prior Kenyan studies that rely on single-equation cross-sectional models with coarse scale indicators (Chelang'a *et al.,* 2021, 2023). The present study's results suggest that farm scale is a weak, stage-specific, and context-dependent predictor of GAP adoption in the Murang'a avocado value chain, and that policy interventions premised on the assumption that larger farms automatically adopt more GAPs are unlikely to be effective in this setting.

5.8.2 To assess the effect of training on the adoption of GAPs among avocado farmers, influencing GAPs adoption

The adoption literature consistently identifies training, extension contact, and access to information as among the most robust predictors of complex practice adoption in African smallholder systems. A systematic review of adoption studies documents consistent positive effects of training and information access on uptake intensity, particularly for innovations that require knowledge and repeated practice (Li *et al.,* 2024). In the Kenyan horticulture context, GLOBALG.A.P. adoption studies similarly report that extension contact and group-based learning lower information costs and significantly increase compliance probabilities (Chelang'a *et al.,* 2023). These findings build on earlier work demonstrating that technical knowledge acquisition, whether through formal training or informal demonstration, is central to bridging the gap between awareness and actual practice adoption in smallholder settings (Nthambi *et al.,* 2013). The present study partially corroborates this body of evidence. The MVP results confirm that training receipt has a positive and statistically significant effect on pre-harvest GAPs adoption, consistent with the finding that information-based interventions are most effective at improving compliance with knowledge-intensive practices that require behavioural change, such as pesticide handling, IPM, and record-keeping during the growing season.

This finding aligns with Chelang'a *et al.* (2023) and Li *et al.* (2024), who document that extension and training services meaningfully improve adoption of standards-linked practices when they reach commercially oriented farmers. These findings speak directly to the methodological critique advanced in the empirical review: that training is frequently operationalized as a binary variable, masking critical variation in training quality, duration, content relevance, and the specific GAP domain addressed, as noted by Chelang'a *et al.* (2023) and Li *et al.* (2024). The present study's results suggest that available training is oriented toward pre-harvest production practices and does not adequately address downstream compliance requirements at harvest and post-harvest stages. This is a novel and policy-relevant finding for the Murang'a avocado context, which the existing literature, inferred from other crops such as beans and pineapple, does not directly address (Nthambi *et al.,* 2013). Accordingly, while the current study confirms the positive role of training for pre-harvest GAPs adoption, it departs from a generalized endorsement of training as a value-chain-wide adoption driver, demonstrating instead that the content gaps and uneven reach of existing programs constrain its effect on harvest and post-harvest compliance.

5.8.3 To assess the influence of contracts with exporter companies on GAPs adoption.

The role of formal contractual arrangements between exporters and smallholder farmers in facilitating the adoption of standards is well established in the African horticulture literature. Exporter contracts are argued to internalize part of the compliance cost burden, through input credit, technical advisory services, payment of certification fees, and guaranteed market access, while simultaneously creating a credible enforcement mechanism that incentivizes sustained compliance (Asfaw *et al.,* 2009, 2022).

In Kenya, research on GLOBALG.A.P.-linked value chains demonstrates that contractual arrangements frequently constitute the primary institutional vehicle through which standards diffuse to smallholders, particularly via group certification and exporter-led training programs (Chelang'a *et al.,* 2021). These findings echo broader evidence from African agricultural value chains showing that buyer governance and monitoring intensity are critical mediators of standards adoption at the farm level (Tallontire *et al.,* 2014).

The results of the present study are broadly consistent with this literature and, in some respects, reinforce it with empirical evidence from a crop and context, Murang'a avocados, for which direct evidence has been absent. The MVP model reveals that contract farming exerts a strong, positive, and highly significant effect on pre-harvest GAPs adoption, with an effect size comparable in magnitude to GlobalG.A.P. certification and sanitation record-keeping, two of the most powerful adoption predictors in the model. Contract farming also has a meaningful and statistically significant positive effect on post-harvest GAPs adoption, consistent with the expectation that exporter contracts enforce downstream compliance requirements around sorting, waste disposal, and hygiene. These findings substantively confirm the conclusions of (Asfaw *et al.,* 2009, 2022; Chelang'a *et al.,* 2021) that exporter-linked contracting is among the most effective institutional levers for raising smallholder compliance with food safety and quality standards.

Notably, however, the effect of contract farming on harvest GAPs adoption is negative and statistically insignificant, a finding that warrants careful interpretation. This finding also draws attention to a methodological weakness identified in the empirical review: the literature's tendency to measure contracts as a simple binary "has contract" dummy, without capturing the heterogeneity of contract terms, price premiums, monitoring intensity, or technical assistance packages that determine the actual compliance incentives embedded in individual agreements (Chelang'a *et al.,* 2021; Tallontire *et al.,* 2014).

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While the present study maintains this binary operationalization due to data constraints, the strong and differentiated effects of contracting across value chain stages suggest that future research should seek richer characterization of contract governance structures to better understand how and when exporter relationships translate into GAPs compliance improvements. Furthermore, the ongoing concern about selection bias, that exporters preferentially contract more capable, better-located, or already-compliant farmers, remains a relevant limitation in the present analysis, consistent with cautions raised by Tallontire *et al.* (2014) and Amare *et al.* (2019), and reinforces the need for quasi-experimental or longitudinal designs in future work on avocado export value chains in Kenya.

5.9 Cross-adoption of GAPs Practices across production stages

The results indicate differing patterns of association between GAPs adoption across production stages. There was no statistically significant relationship between pre-harvest and post-harvest GAPs adoption, with similarly high proportions of post-harvest adoption among both pre-harvest non-adopters and adopters. In contrast, a strong and statistically significant association was found between harvest and post-harvest GAPs. Farmers who adopted harvest GAPs were more likely to adopt post-harvest practices than those who did not. These findings suggest that adoption continuity is more pronounced between harvest and post-harvest stages than between pre-harvest and post-harvest stages. This finding validates the choice of the multivariate probit specification over separate univariate probits and is consistent with the theoretical expectation, implicit in the behavioural adoption literature, that farmers approach compliance as a portfolio of interrelated decisions rather than a series of isolated binary choices (Lippe & Grote, 2017). The non-significant correlation between pre-harvest and post-harvest adoption, however, suggests that the sequential interdependence is localized to adjacent value chain stages, a nuance that prior single-equation adoption studies which dominate the Kenyan horticulture literature, are structurally unable to detect.

5.10 Distribution of GAPs scores

5.10.1 Distribution of GAPs scores among avocado farmers

The clustering of pre-harvest GAPs scores at moderate-to-high levels reflects heterogeneity in adoption depth characteristic of complex practice bundles, where uptake is shaped by variation in knowledge access, resource endowments, and institutional incentives (Wossen *et al.,* 2017). The near-universal attainment of maximum harvest GAPs scores indicates that harvest-stage compliance has effectively reached saturation in the study population, creating a ceiling effect that limits further quality differentiation at this stage. The high concentration of post-harvest scores at the upper end must be interpreted with caution in light of the critical compliance gaps documented in the adoption portfolio. The high aggregate scores likely reflect compliance with more accessible practices, such as sorting and crating, rather than with the most infrastructurally demanding requirements such as proper produce storage and washing. This discrepancy highlights a limitation of aggregate GAPs scoring approaches that may obscure critical within-stage variation in the depth of compliance (Graffham *et al.,* 2017).

5.10.2 Mean differences in production outcomes by GAPs adoption status

The superior export share and Grade 1 produce proportions observed among high GAPs adopters provide empirical support for the proposition that GAPs compliance constitutes a source of market-relevant quality differentiation in smallholder export horticulture (Asfaw *et al.,* 2010; Swinnen & Vandemoortele, 2009). The systematic implementation of pre-harvest, harvest, and post-harvest GAPs reduces the incidence of physical damage, chemical residue exceedances, and hygienic contamination that are the primary drivers of export rejection and grade downgrading. The attenuation of the performance differential in the current season may reflect convergence among previously low-adopting farmers through social learning and knowledge diffusion (Kondylis *et al.,* 2017). Alternatively, the lagged nature of quality benefits from practices operating over multi-year time horizons, such as soil health management, may mean that compliance effects are not fully observable within a single season (Wossen *et al.,* 2017). The consistently tighter performance distribution among high GAPs adopters further underscores that compliance is associated not only with higher average outcomes but also with reduced outcome variability, a dimension of agricultural performance that is particularly consequential for smallholder livelihoods given their inherent exposure to income risk (Muriithi & Matz, 2015).

5.11 Conclusions

5.11.1 Influence of land size on GAPs adoption

In relation to the objective of assessing the influence of farm size, the study concludes, with the qualifications discussed above, that farm size does not operate as a consistent, positive driver of GAPs adoption within this sample. Its only statistically significant association, with pre-harvest adoption, is negative and weak, and runs counter to the dominant expectation in the standards-adoption literature. However, given the narrow range of farm sizes observed and the sample's geographic concentration, this conclusion is most defensibly stated as:

within the range of smallholder avocado farm sizes observed in this commercially integrated production zone, larger avocado area is, if anything, weakly associated with lower pre-harvest GAPs adoption, and farm size shows no detectable association with harvest or post-harvest adoption. This is a narrower and more defensible claim than "farm size is not a driver of GAPs adoption" in general, and avoids overstating a cross-sectional, range-restricted result as a general theoretical finding.

5.11.2 Effect of training on the adoption of GAPs

In relation to the objective of assessing the influence of training, the study concludes that training, as measured by a binary "received GAPs-related training" indicator, is positively and significantly associated with pre-harvest GAPs adoption, but shows no detectable association with harvest or post-harvest adoption. This finding should not be read as "training is ineffective for downstream practices" in a general sense. The available descriptive evidence indicates that the training farmers report receiving is itself heavily weighted toward pre-harvest-relevant content and rarely covers post-harvest management or record-keeping. The more defensible conclusion is that the training currently reaching this farmer population is concentrated in pre-harvest content, and its measured effect is correspondingly concentrated in pre-harvest outcomes; whether training with different content, specifically post-harvest-focused, would be effective for post-harvest adoption is a question this study's data cannot answer, because too few farmers have received such training to estimate its effect with any precision.

5.11.3 Participating in avocado contract farming on adoption of GAPs

In relation to the objective of assessing the influence of contract farming, the study concludes that formal contract farming with exporters is positively and significantly associated with both pre-harvest and post-harvest GAPs adoption, with no detectable association for harvest-stage adoption, a result attributable to near-ceiling adoption of harvest practices rather than to contracts being irrelevant at that stage. Given the high correlation between contract status and certification observed in this sample, this finding is best understood as evidence that integration into formal export-chain governance, of which contracting is one observable marker, is associated with higher pre-harvest and post-harvest compliance, rather than as isolating "contracts" as a uniquely identifiable lever distinct from certification, group registration, or extension access, all of which are similarly positively associated with adoption and similarly correlated with one another.

5.11.4 Contributions of the study results

This study makes the following contributions, distinguished here between what is empirically demonstrated and what remains conceptual.

Empirical contribution. This study provides a practice-disaggregated (pre-harvest, harvest, post-harvest) farm-level econometric analysis of GAPs adoption determinants specific to avocado farming, addressing a gap in the literature where prior Kenyan evidence on farm size, training, and contract effects on standards adoption is drawn primarily from other crops. The disaggregation by production stage, rather than a single composite "compliance" score, is itself a contribution, since it reveals that determinants operate differently across stages, a pattern that would be invisible in a single-equation, aggregate-compliance approach.

Methodological contribution. The study demonstrates, via significant cross-equation correlations between the three adoption equations, that pre-harvest, harvest, and post-harvest GAPs adoption decisions are not independent, providing an empirical basis, rather than a purely conceptual one, for the use of multivariate rather than single-equation probit models in future GAPs adoption research in similar contexts. This is a more modest, but more defensible, claim than asserting that the study "validates" a particular behavioural theory of adoption; the cross-equation correlations are consistent with a portfolio-decision framing of adoption but do not, on their own, distinguish it from alternative explanations, such as shared exposure to a common institutional actor.

Contextual contribution to the policy evidence base. By documenting that institutional variables (contracts, certification, extension) show stronger and more consistent associations with GAPs adoption than farm size, within a commercially integrated production zone, the study provides an evidence base specifically relevant to similar zones, export-linked, cooperative-served avocado production areas, narrower in scope than a county-wide claim but more precise for the contexts it does cover.

Methodological findings as a contribution in their own right. The study's own measurement findings, particularly the divergence between farm-area and tree-count effects, and the composition issue in the training variable, constitute a methodological contribution: they identify specific, testable hypotheses about why cross-sectional adoption studies in this literature may produce inconsistent farm-size and training results, demonstrating concretely, with this study's own data, how such inconsistencies can arise from measurement choices rather than from genuine differences in underlying relationships.

5.12 Recommendations

The recommendations below are organised by the specific gap or limitation that motivates each, with a brief feasibility note addressing institutional and resource realities for each one.

5.12.1 Addressing the post-harvest infrastructure gap

County and national government, in partnership with cooperatives, should prioritise shared, low-cost post-harvest infrastructure, such as covered or shaded storage points and washing stations at existing cooperative collection points in commercially active production zones, rather than relying on individual farm-level investment.

This is prioritised as the highest-effect, lowest-behavioural-dependency recommendation, because the post-harvest gap identified in this study is concentrated in infrastructure-dependent practices (storage, washing) rather than knowledge-dependent ones, meaning the intervention does not depend on first changing farmer behaviour or training uptake. However, it requires capital investment and coordination between county government and cooperatives. A feasible starting point would be shaded or ventilated storage rather than full cold-chain investment, given the small scale of most holdings and the likelihood that full cold-chain infrastructure exceeds near-term resource availability for county-level programmes.

5.12.2 Realigning training content with post-harvest and record-keeping gaps

Given that private-sector training providers dominate and are plausibly incentivised to focus on pre-harvest, input-linked content, the most feasible near-term intervention is not "more training" in general, but a targeted requirement, negotiated through existing exporter-cooperative relationships, that a defined minimum share of contracted farmers' training hours cover post-harvest handling and record-keeping.

This is prioritised above a general "expand government extension" recommendation because government extension access is currently very low, and scaling it to reach the substantial share of farmers not currently accessing any GAPs-relevant training would require substantial new public investment in extension staffing, a resource-intensive undertaking with a long implementation horizon. Working through existing private-sector training channels, redirecting a portion of existing training activity toward post-harvest content, is more immediately actionable, though it depends on exporters and cooperatives perceiving sufficient commercial benefit, such as reduced rejection rates, to justify the content shift.

5.12.3 Strengthening record-keeping at the institutional rather than individual level

Rather than recommending that individual farmers prioritise record-keeping, cooperatives and certification bodies should be supported to audit and strengthen centralised record-keeping systems, given the possibility that documentation for certified farmers may already be substantially managed at the cooperative or exporter level. This recommendation is explicitly conditional: it should be preceded by a small-scale verification exercise, such as a targeted follow-up survey or key-informant interviews with a small number of cooperatives, to establish whether the centralised-record-keeping hypothesis holds, before committing resources to either individual-farmer training, if records genuinely are absent at all levels, or institutional audit support, if records exist centrally but were not captured by this farm-level survey.

5.12.4 Addressing the contract-farming and certification overlap in future programme design

Programmes seeking to expand contract farming should recognise that, in this sample, contract status and certification are highly correlated and may reflect a single underlying institutional relationship rather than two independent levers. Expansion efforts should therefore be designed and evaluated as expanding integration into formal export-chain governance as a bundle, contract plus certification plus associated training and extension, rather than assuming that contracts alone, absent the accompanying certification and extension support typically bundled with them, would replicate the adoption effects estimated here. This is less a standalone action item than a design caveat for any programme implementing the recommendations above, included to prevent a likely implementation error: offering "contracts" without the bundled support that this study's data suggest typically accompanies them in practice.

5.12.5 Research priorities arising from this study's limitations

Future research should prioritise: sub-county-stratified sampling to test whether the farm-size and training findings hold outside the commercially integrated zone from which this sample was drawn; a supplementary specification using topic-specific training variables, particularly post-harvest management training, to test the composition explanation for the training non-result; key-informant interviews with cooperatives and exporters to verify the centralised record-keeping hypothesis and provide triangulation currently absent from this study; and a small enumerator-observation sub-study, even on a subsample, to benchmark self-reported adoption against observed practice for a handful of checkable items, such as the presence of sanitation logs or crates, to quantify the potential self-report bias affecting the descriptive results.

5.13 Suggestion for areas of further research

- **Quasi-experimental and longitudinal studies** to establish causal links between contract farming, training, and GAP adoption, addressing the selection bias concerns raised.
- **Heterogeneity of contract terms**: Future research should move beyond binary "has contract" variables to capture contract duration, price premium levels, monitoring intensity, and technical assistance packages to determine which specific contract features most effectively drive GAPs compliance.
- **Post-harvest technology adoption**: Given the critically low adoption of proper storage and washing, research should evaluate the cost-effectiveness and farmer acceptance of low-cost post-harvest technologies (evaporative cooling chambers, plastic crates, waxing) relative to capital-intensive cold-chain solutions.
- **Training content and delivery mechanisms**: Experimental studies comparing the effectiveness of different training modalities (farmer field schools, digital extension, peer-to-peer learning, demonstration plots) on GAPs adoption across all three production stages.
- **Gender and generational dynamics**: Further investigation into why female farmers have lower participation in contract farming and certification, and whether targeted interventions can close the gender gap in GAPs compliance.

The findings presented in this chapter, and the conclusions, describe patterns observed among avocado farmers in Kandara sub-county, which accounts for 83.24% of the achieved sample (Table 4.2). This concentration has several implications that qualify how the results should be read and applied. First, Kandara is one of the more commercially integrated, exporter-linked production zones in Murang'a County, hosting a relatively dense network of cooperatives, packhouses, and collection centres. The near-universal export orientation (98.85%) and the relatively high rates of contract farming and GlobalG.A.P. certification observed in this sample are therefore likely to be, at least in part, features of Kandara's institutional environment rather than features of avocado farming in Murang'a County as a whole. Farmers in less commercially integrated sub-counties, such as Mathioya, Kangema, or Murang'a East, which together account for under 2% of the sample, may face a substantially different institutional landscape, with less exporter presence, fewer contract opportunities, and lower certification rates, and the determinants of GAPs adoption identified here (contract farming, certification, private extension) may operate differently, or be largely absent as options, in those areas.

Second, this has specific implications for the policy recommendations. Recommendations premised on expanding contract farming and exporter linkages are most directly applicable to areas with an existing exporter presence; in sub-counties where this institutional infrastructure does not yet exist, the prior step of establishing such linkages would itself be the binding constraint, a different policy problem from the one this study's data can speak to. Third, the study's findings are best framed as describing GAPs adoption dynamics within a commercially integrated avocado production zone, providing a depth of evidence for such zones that is valuable in its own right, given that these are also the zones from which most current export volume originates, rather than as a representative county-wide assessment. Future research explicitly sampling across sub-counties with varying degrees of commercial integration, ideally with stratification to ensure adequate representation of less-integrated areas, would be needed to assess whether the determinants identified here generalise, and this is added as a priority area for further research.

5.14 Study limitations

Endogeneity in training and contract variables. Training and contract status are plausibly endogenous to unobserved farmer characteristics, such as motivation, managerial ability, or prior commercial orientation, that also affect GAPs adoption directly. As a consequence, the significant coefficients on training and contract farming cannot be interpreted as the effect of providing training or a contract to a randomly selected farmer; they may partly reflect that farmers who were already more compliance-oriented were also more likely to receive training or be offered contracts. The policy recommendations in this chapter should therefore be understood as describing associations between adoption and integration into formal support structures, not as guaranteed returns to expanding those structures to a different population of farmers. Measurement error in farm-size and training variables. As discussed above, the farm-size result may be sensitive to the narrow range of farm sizes observed and to the divergence between area- and tree-count-based scale measures, and the training result may be attenuated by the content composition of the binary training variable.

As a consequence, the conclusions regarding farm size and training should be read as conditional on this study's specific operationalisation of these variables, not as general findings about scale or training effects in avocado adoption research more broadly.

Sampling imbalance since achieved sample is heavily concentrated in one sub-county. As a consequence, the study's findings most directly describe adoption dynamics in a commercially integrated, exporter-linked production zone; the extent to which farm-size, training, and contract effects generalise to less commercially integrated areas cannot be assessed with this data, and recommendations premised on expanding institutional structures may not transfer directly to areas where those structures do not yet exist at all.

Self-reported adoption and outcome data where all GAPs adoption indicators and production and income figures are farmer self-reports without independent verification. As a consequence, the gap between high adoption of "checkable" practices, such as pesticide dosage compliance, and low adoption of less-checkable practices, such as sanitation records, may be partly an artefact of differential social-desirability bias rather than purely a true compliance difference, meaning the true magnitude of the pre-harvest administrative compliance gap could be larger or smaller than reported, and this cannot be determined from the available data.

Cross-sectional design and direction of association, where statistically significant cross-equation correlations and cross-adoption associations establish that adoption decisions across stages are related, but not which, if any, causally influences the other, nor whether both are driven by an unobserved third factor. As a consequence, any "bridge" interpretation linking adoption at one stage to adoption at another is one plausible reading among several, and the policy implication that intervening at one stage would improve outcomes at another is not directly supported by correlational evidence alone.

Limited triangulation since the qualitative component of this study did not provide an independent data source against which the institutional-level explanations offered in this chapter, such as the hypothesis that record-keeping is centralised at cooperative level, or that private training content is shaped by input-supplier incentives, can be checked. As a consequence, these explanations remain plausible interpretations consistent with the quantitative patterns, but are not independently corroborated, and should be presented as hypotheses for further research rather than as established findings.

5.15 Chapter summary

This chapter presents the discussion derived from the descriptive and inferential statistics. The discussion covers the response rate, respondents' demographic characteristics, descriptive statistics, diagnostic test outcomes, and the results of correlation and regression analyses. The chapter concludes with conclusions and recommendations.

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Appendix

Appendix 1: National Commission for Science, Technology and Innovation (NACOSTI) Permit Ref No: 629894

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **629894**

Date of Issue: **19/May/2026**

RESEARCH LICENSE

This is to Certify that Mr.. KEVIN MWANGI NJOKA of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Muranga on the topic: The Influence of Farmer Awareness on Adoption of Good Agricultural Practices in Avocado Farming in Murang'a County for the period ending : 19/May/2027.

License No: **NACOSTI/P/26/4189216**

629894

Applicant Identification Number

Ag. Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

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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;
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    - 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
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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 2: Ethical Approval from Strathmore SU-ISERC

Strathmore
UNIVERSITY

3rd April 2026

Mr Njoka Kevin,
kevin.njoka@strathmore.edu

Dear Mr Njoka,

RE: The Influence of Farmer Awareness on Adoption of Good Agricultural Practices in Avocado Farming in Murang'a County

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC3467/26.** The approval period is from **3rd April 2026 to 2nd April 2027.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, and 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 affect the 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 3: Questionnaire

Ethical Consent

Hello, my name is [Your Name], and I am working with Mavuno / KTL / The Fresh Produce. We are carrying out a survey as part of a comprehensive baseline study of the avocado sector in Kenya. This research has received approval from the National Commission for Science, Technology and Innovation (NACOSTI) under permit number [NACOSTI Ref No: 629894].

Participation is entirely voluntary. The interview will last approximately [30–40 minutes], and you can choose not to answer any question or stop the interview at any time without penalty or loss of benefits. The information you share will be used solely for research to better understand avocado production and Good Agricultural Practices. All responses will be kept strictly confidential. Your name will not appear in any reports, and your answers will be combined with those of other participants. The data will be securely stored, accessed only by the research team, and used exclusively for academic and policy analysis. No individual household or farmer will be identifiable in any publication or presentation. If you agree to participate, I will continue with the interview. Do you consent to take part in this study?

The survey aims to:

1. Assess farm compliance with **Sanitary and Phytosanitary Standards (SPS)**, which are essential for accessing Chinese and other global markets.
2. Identify gaps in the adoption of key **Integrated Pest Management (IPM)** practices and determine farmers' needs for training, resources, and technical assistance.
3. Evaluate Kenya's current **export potential to China** to inform targeted interventions that enhance market access and increase export volumes.

You have been randomly selected to participate in this survey.
However, participation is **voluntary**, and all responses will remain **confidential**.

Are you willing to participate?

☐ Yes ☐ No

If *Yes*, the Agronomist should proceed with the survey.
If *No*, the Agronomist should thank the farmer and select another respondent from the sampling frame.

SECTION 1.0: FARMER IDENTIFICATION & DEMOGRAPHICS

1A. Farmer Identification

1.1 Company Name

☐ Mavuno ☐ KTL ☐ The Fresh Produce

1.2A. Enumerator Name – Mavuno

☐ Joseph Kiamba ☐ Daniel Njuguna Njoki ☐ Lenity Muthoni

☐ Silvia Achieng ☐ Naphtali Njogu Irungu ☐ David Mumo Munyasya

☐ Samuel Opondo Juma ☐ Jamleck Kihara Nganga ☐ Dennis Kariuki Kinyua

☐ Martin Muthii Kinyua ☐ Other (Specify) ___________

1.2B. Enumerator Name – KTL

☐ Judith Okumu ☐ Margaret Kiarie ☐ Holystar Kibet ☐ Moses Kwemboi

☐ Gilbert Kwemoi Mutai ☐ Walter Muriithi ☐ Obino David Nyambane

☐ Joseph Kibe ☐ Ann Nakhumicha ☐ Other (Specify) ___________

1.2C. Enumerator Name – The Fresh Produce

☐ Juliet Zakari ☐ Gabriel Macharia ☐ Mary Karechu ☐ Ezra Yama

☐ Harun Mwangi ☐ Curtis Mugambi ☐ Wilson Mungoo ☐ Other (Specify) ___________

1.3 County

☐ Meru ☐ Nyeri ☐ Murang'a ☐ Kiambu ☐ Trans Nzoia ☐ Uasin Gishu

☐ Nakuru ☐ Bomet ☐ Kakamega ☐ Bungoma

Farm ID/Code: ___________

1.4 Sub-County (Select according to County)

(Include the specific sub-county list per county as provided.)

1.5 Ward: ___________

1.6 Village: ___________

1.7 Do you operate as:

☐ Independent Farmer ☐ Company Farm

1.8 Respondent relationship to household head / business owner

☐ Household Head ☐ Spouse ☐ Offspring ☐ Relative ☐ Employee ☐ Other (Specify) ___________

1.9 Respondent Name (Three Names, in CAPITAL LETTERS): ___________

Farmer Characteristics

1.10 Farmer's Name (Three Names, in CAPITAL LETTERS): ___________

1.11 Gender: ☐ Male ☐ Female

1.12 Age: ___________

1.13 Formal Education Level:

☐ None ☐ Primary ☐ Secondary ☐ Tertiary ☐ Graduate ☐ Post-Graduate

1.14 Experience in avocado farming (Years): ___________

Business Characteristics

1.15 Name of Avocado Business: ___________

1.16 Business Ownership:

☐ Female-Owned ☐ Male-Owned ☐ Mixed-Gender Partnership

☐ Men-Owned Partnership ☐ Women-Owned Partnership

1.17 Years of Operation: ___________

1.18 Legal Status: ☐ Registered ☐ Not Registered

1.19 Business Size:

☐ Micro (1–5 Employees) ☐ Small (5–50) ☐ Medium (50–200) ☐ Large (200+)

1.20 Contact Number: ___________

1.21 GPS Coordinates:

Latitude _____ Longitude _____ Altitude (m) _____ Accuracy (m) _____

Data Collection Date & Time: ___________

1B. Registration Details

1.22 Orchard/Farm Name: ___________

1.23 Registration Code (If not registered, write "None"): ___________

1.24 Is this orchard registered as part of a group? ☐ Yes ☐ No

1.25 KEPHIS Registration Status: ☐ Yes ☐ No

1.26 GACC (China) Approval Status: ☐ Yes ☐ No

1.27 Other Registration (Specify): ___________

1.28 Most Recent Year of Registration: ___________

SECTION 2.0: FARM CHARACTERISTICS

2.1 Total Farm Size (Acres): ___________

2.2 Total Area Under Avocado (Acres): ___________

2.3 Number of Avocado Trees: ___________

2.4 Age Distribution of Trees

☐ 0–3 years ☐ 4–7 years ☐ 8+ years

- 2.41 Trees (0–3 yrs): _____
- 2.42 Trees (4–7 yrs): _____
- 2.43 Trees (8+ yrs): _____

2.5 Source of Seedlings:

☐ Licensed Nursery ☐ Non-Licensed Nursery ☐ Own Farm ☐ Other (Specify) _____

SECTION 3.0: AVOCADO PRODUCTION PRACTICES

3A. Orchard Management

3.1 Variety Grown: ☐ Hass ☐ Fuerte ☐ Puebla ☐ Pinkerton ☐ Nabal ☐ Reed ☐ Booth 7 ☐ Ettinger ☐ Bacon ☐ Gwen ☐ Other (Specify) _____

3.2 Are Good Agricultural Practices (GAP) applied? ☐ Yes ☐ No

3.3 Type of Fertilizer Used: ☐ Organic ☐ Inorganic ☐ None

3.31 Fertilizer Physical Form and Application Quantity

Q3.31 What is the **physical form** of the fertilizer used on your avocado trees?

☐ Liquid ☐ Solid ☐ Both

If Liquid:

Q3.311 Indicate the **annual quantity of *liquid organic fertilizer*** used **per tree** (in **liters**):

__________ liters/tree/year

Q3.313 Indicate the **annual quantity of *liquid inorganic fertilizer*** used **per tree** (in **liters**):

__________ liters/tree/year

If Solid:

Q3.312 Indicate the **annual quantity of *solid organic fertilizer*** used **per tree** (in **kilograms**):

__________ kg/tree/year

Q3.314 Indicate the **annual quantity of *solid inorganic fertilizer*** used **per tree** (in **kilograms**):

__________ kg/tree/year

✅ **Enumerator Note:** Ensure the farmer understands the difference between *organic* (manure, compost, etc.) and *inorganic* (chemical) fertilizers before recording responses.

3.4 Soil Conservation Measures: ☐ Mulching ☐ Terracing ☐ Cover Cropping ☐ Other (Specify) _____

3.5 Irrigation Practices: ☐ Rainfed ☐ Drip ☐ Sprinkler ☐ Manual ☐ None ☐ Other (Specify) _____

3.6–3.8 IPM and Sanitation Practices – include Yes/No checkboxes and sub-items (as originally listed).

Sanitation and Field Hygiene

Q3.6 Is there a record of sanitation conditions maintained on the farm?

☐ Yes ☐ No

Q3.7 Is there prompt elimination of dropped fruits from the orchard?

☐ Yes ☐ No

Integrated Pest Management (IPM)

Q3.8 Is an **Integrated Pest Management (IPM)** program implemented on the farm?

☐ Yes ☐ No

If *Yes*, specify the **methods used**:

Pest Monitoring

Q3.81 Is pest monitoring conducted on the farm?

☐ Yes ☐ No

Q3.811 If *Yes*, is pest monitoring conducted under **KEPHIS** guidance?

☐ Yes ☐ No

Chemical Control

Q3.82 Are chemical control methods used for pest management?

☐ Yes ☐ No

If *Yes*, provide the following details:

Q3.821 Name of chemical: ____

Q3.822 Active ingredient: ____

Q3.823 Dosage applied: ____

Q3.824 Time of application:

☐ Morning ☐ Afternoon ☐ Evening

Q3.825 Frequency of spraying:

☐ Daily ☐ Weekly ☐ Biweekly ☐ Monthly ☐ Bi-annually ☐ Annually ☐ Other (specify): ____________________

Biological Control

Q3.83 Are biological control methods applied?

☐ Yes ☐ No

If *Yes*, specify:

Q3.831 Biological agent(s) used: _____________________________________

Q3.832 Density of application: _______________________________________

Fly Traps

Q3.84 Are fly traps installed in the orchard?

☐ Yes ☐ No

Q3.841 Number of traps installed: ___________

Q3.8411 Type(s) of traps used:

☐ Ceratitis ☐ Whitefly ☐ Persea mites ☐ Other (specify): ____________________

Q3.8412 Are the traps active and monitored regularly?

☐ Yes ☐ No

Q3.85 Specify any **other IPM methods** implemented:

3B. Control Measures for Quarantine Pests

Q3.9 Are fruit flies and False Codling Moth (FCM) controlled through IPM practices?

☐ Yes ☐ No

If *Yes*, specify the methods used:

Q3.91 Fly traps used? ☐ Yes ☐ No

Q3.92 Chemical control used? ☐ Yes ☐ No

Q3.93 Biological control used? ☐ Yes ☐ No

Q3.94 Mating disruption applied? ☐ Yes ☐ No

Q3.95 Other (specify): ____

Q3.10 Are scales and other quarantine pests monitored **bi-weekly from blooming to harvest**?

☐ Yes ☐ No

Q3.11 If pests or symptoms are detected, are **appropriate control measures** applied immediately?

☐ Yes ☐ No

If *Yes*, specify:

Q3.111 Biological control applied? ☐ Yes ☐ No

Q3.112 Chemical control applied? ☐ Yes ☐ No

✅ **Enumerator Note:** Ensure the farmer understands the difference between *biological*, *chemical*, and *cultural* control methods. Verify consistency between IPM implementation and pest management practices.

SECTION 4.0: PRODUCTIVITY & HARVESTING

Break into "Last Season" and "This Season" subsections as in your text, with all yield, losses, causes, and harvesting method questions clearly separated.

Last Season (Previous Harvest Year)

Q4.1 Average yield per avocado tree aged **0–3 years** last season (in kilograms):

_________ kg/tree

Q4.11 Average yield per avocado tree aged **4–7 years** last season (in kilograms):

_________ kg/tree

Q4.12 Average yield per avocado tree aged **8 years and above** last season (in kilograms):

_________ kg/tree

Q4.2 Total avocado harvest last season (in kilograms):

_________ kg

Q4.3 Total avocado losses last season (in kilograms):

_________ kg

Q4.31 Primary cause of loss last season:

☐ Bruising ☐ Disease ☐ Poor Handling ☐ Theft ☐ Other (specify):

____

Q4.32 Other causes of loss last season:

☐ Bruising ☐ Disease ☐ Poor Handling ☐ Theft ☐ Other (specify):

____

This Season (Current Harvest Year)

Q4.4 Average yield per avocado tree aged **0–3 years** this season (in kilograms):

_________ kg/tree

Q4.41 Average yield per avocado tree aged **4–7 years** this season (in kilograms):

_________ kg/tree

VT OMNES VNVM SINT

Q4.42 Average yield per avocado tree aged **8 years and above** this season (in kilograms):

_________ kg/tree

Q4.5 Total avocado harvest this season (in kilograms):

_________ kg

Q4.6 Total avocado losses this season (in kilograms):

_________ kg

Q4.7 Primary cause of loss this season:

☐ Bruising ☐ Disease ☐ Poor Handling ☐ Theft ☐ Other (specify):

____

Q4.71 Other causes of loss this season:

☐ Bruising ☐ Disease ☐ Poor Handling ☐ Theft ☐ Other (specify):

____

Yield and Harvest Details

Q4.8 Average number of fruits per avocado tree aged **0–3 years**:

_________ fruits/tree

Q4.81 Average number of fruits per avocado tree aged **4–7 years**:

_________ fruits/tree

Q4.82 Average number of fruits per avocado tree aged **8 years and above**:

_________ fruits/tree

Harvesting and Post-Harvest Practices

Q4.9 Harvesting method used:

☐ Hand-Picking ☐ Pole with Basket ☐ Other (specify): ____________________

Q4.10 Harvesting timing (maturity stage of fruits):

☐ Mature ☐ Immature ☐ Overripe

Q4.11 Post-harvest handling practices applied:

☐ Proper Storage ☐ Washing ☐ Use of Crates ☐ Sorting ☐ None ☐ Other (specify): ____________________

VT OMNES VNVM SINT

Enumerator Note:

Record all quantities in kilograms. Ensure that "last season" and "this season" are clearly defined in terms of production year. Confirm that losses and harvest figures correspond logically to the average yields reported.

SECTION 5.0: MARKET ACCESS & INCOME

Maintain "Last Season" and "This Season" structure with sub questions (5.1–5.10). Include checkboxes for Market Outlet, list of avocado varieties with price fields, total income, and challenges.

Q5.1 What is your **main market outlet** for avocado sales?

☐ Local Market ☐ Export ☐ Marketing Agents ☐ Processor ☐ Other (specify): ______________________

Last Season (Previous Harvest Year)

Q5.2 Average selling price of **Hass** variety per kilogram last season (KSH): __________ KSH/kg

Q5.21 Average selling price of **Fuerte** variety per kilogram last season (KSH): __________ KSH/kg

Q5.22 Average selling price of **Puebla** variety per kilogram last season (KSH): __________ KSH/kg

Q5.23 Average selling price of **Pinkerton** variety per kilogram last season (KSH): __________ KSH/kg

Q5.24 Average selling price of **Nabal** variety per kilogram last season (KSH): __________ KSH/kg

Q5.25 Average selling price of **Reed** variety per kilogram last season (KSH): __________ KSH/kg

Q5.26 Average selling price of **Booth 7** variety per kilogram last season (KSH): __________ KSH/kg

Q5.27 Average selling price of **Ettinger** variety per kilogram last season (KSH): __________ KSH/kg

Q5.28 Average selling price of **Bacon** variety per kilogram last season (KSH):

_________ KSH/kg

Q5.29 Average selling price of **Gwen** variety per kilogram last season (KSH):

_________ KSH/kg

Q5.30 Average selling price of **other avocado varieties** per kilogram last season (KSH):

_________ KSH/kg

Q5.3 Total income from avocado sales last season (KSH):

_________ KSH

Q5.4 What proportion of your harvest did you sell as **Grade 1** last season?

_________ %

Q5.5 What proportion of your harvest did you retain for **own use or gifting** last season?

_________ %

This Season (Current Harvest Year)

Q5.6 Average selling price of **Hass** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.61 Average selling price of **Fuerte** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.62 Average selling price of **Puebla** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.63 Average selling price of **Pinkerton** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.64 Average selling price of **Nabal** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.65 Average selling price of **Reed** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.66 Average selling price of **Booth 7** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.67 Average selling price of **Ettinger** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.68 Average selling price of **Bacon** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.69 Average selling price of **Gwen** variety per kilogram this season (KSH):

_________ KSH/kg

Q5.70 Average selling price of **other avocado varieties** per kilogram this season (KSH):

_________ KSH/kg

Q5.7 Total income from avocado sales this season (KSH):

_________ KSH

Q5.8 What proportion of your harvest did you sell as **Grade 1** this season?

_________ %

Q5.9 What proportion of your harvest did you retain for **own use or gifting** this season?

_________ %

Q5.10 What are the main **challenges in market access** you experienced?

☐ Price Fluctuations ☐ Limited Buyers ☐ Quality Standards ☐ Other (specify):

____

SECTION 6.0: COMPLIANCE WITH SPS & GLOBAL GAP REQUIREMENTS

Include all questions 6.1–6.8, organized under:
- Training and Certification
- Record Keeping
- Sanitation Practices
- Pest and Disease Management

Each should retain Yes/No checkboxes and spaces for "Other (Specify)."

6.1 Training on SPS & Compliance Received

☐ Yes ☐ No

6.2 Certifications the Orchard is Compliant with This Season

☐ None

☐ Global GAP

☐ KEPHIS / China Market Certification

☐ FairTrade

☐ Organic

☐ Other (specify): ______________________

6.3 Record-Keeping Practices

Which of the following records are maintained at the orchard? (Select all that apply)

☐ Farm Logs ☐ Input Records

☐ Harvest Records ☐ Hygiene Records

☐ Pest Control Records ☐ PPE Cleaning Logs

☐ Training Records ☐ Workers' Contracts

☐ Employee Policy ☐ Safety Procedures

☐ Water, Soil & Manure Records ☐ Contract File

☐ Human Rights Policy ☐ Sales Records

☐ Waste Disposal Records ☐ Manure Application

☐ Wage Records ☐ Truck Cleaning

☐ Delivery Records ☐ Pruning Logs

☐ Scouting Logs ☐ None

☐ Other (specify): ______________________

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Sanitation Practices Observed at the Orchard

6.4 Use of Clean Harvesting Tools

☐ Yes ☐ No

6.5 Proper Disposal of Waste

☐ Yes ☐ No

6.6 Compliance with Pesticide Withdrawal Period (REI / PHI)

☐ Yes ☐ No

Pest and Disease Management Compliance

6.7 Use of Approved Pesticides Only

☐ Yes ☐ No

6.8 Application of Correct Dosage

☐ Yes ☐ No

SECTION 7.0: SUSTAINABILITY & ENVIRONMENTAL IMPACT

Questions 7.1–7.5, with subcategories for:

- Water Sources
- Waste Management
- Biodiversity Conservation
- Other Value Chains (with specification fields)

7.1 Water Source for Irrigation

☐ None
☐ River
☐ Borehole
☐ Rainwater Harvesting
☐ Other (specify): ______________________

7.2 Waste Management Practices

☐ Composting
☐ Burning
☐ Dumping
☐ Other (specify): ______________________

7.3 Biodiversity Conservation Practices

☐ Agroforestry
☐ Pollinator Habitats
☐ Soil Cover Crops
☐ Other (specify): ______________________

7.4 Other Trees Planted Around or Within the Orchard

☐ Grevillea
☐ Cupressus
☐ Moringa oleifera
☐ Casuarina
☐ Other (specify): ______________________

7.5 Other Value Chains the Farmer is Involved In

☐ Dairy Farming
☐ Poultry Farming
☐ Crop Farming
☐ Other (specify): _______________________

7.51 If Crop Farming, Specify Crop(s):

SECTION 8.0: TRAINING & SUPPORT RECEIVED

Include questions 8.1–8.6, organized under:

- Training Received
- Extension Services
- Training Needs

8.1 Training Received in the Last Year

☐ Good Agricultural Practices (GAP)
☐ Post-Harvest Management
☐ Certification Compliance
☐ Market Access
☐ Other (specify): _______________________

8.2 Training Received in the Last 6 Months

☐ Good Agricultural Practices (GAP)
☐ Post-Harvest Management
☐ Certification Compliance
☐ Market Access
☐ Other (specify): _______________________

8.3 Source of Training

☐ Government
☐ Private Sector
☐ Cooperative / NGO
☐ None
☐ Other (specify): ______________________

8.4 Extension Services Accessed

☐ Government
☐ Private Sector
☐ Cooperative / NGO
☐ None
☐ Other (specify): ______________________

8.5 Source of Extension Services

☐ Government
☐ Private Sector
☐ Cooperative / NGO
☐ None
☐ Other (specify): ______________________

8.6 Most Pressing Training or Extension Needs

☐ Good Agricultural Practices (GAP)
☐ Post-Harvest Management
☐ Certification Compliance
☐ Market Access
☐ Other (specify): ______________________

Suggestions for the SHAPE Program Improvement

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____

____

END OF SURVEY

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Appendix 4: Categorization of Good Agricultural Practices (GAPs)

Category	Questionnaire Items (Variable Source)	Measurement
Pre-Harvest GAPs	Application of GAPs in the orchard	Yes/No
	Type of fertilizer used (Organic, Inorganic, None)	Categorical
	Soil conservation measures (Mulching, Terracing, Cover cropping, Other)	Multiple response
	Irrigation practices (Rainfed, Drip, Sprinkler, Manual, None)	Categorical
	Record of sanitation conditions	Yes/No
	Prompt elimination of dropped fruits	Yes/No
	Integrated Pest Management (IPM) program implementation	Yes/No
	Pest monitoring (including under KEPHIS guidance)	Yes/No
	Chemical control	Yes/No
	Biological control	Yes/No
	Use of fly traps	Yes/No
	Other IPM practices	Yes/No
	Control of fruit flies and false codling moth	Yes/No
	Control of scales and other quarantine pests	Yes/No
	Immediate application of control measures when pests are found	Yes/No
	Use of approved pesticides only	Yes/No
	Application of correct pesticide dosage	Yes/No
	Waste management practices (Composting, Burning, Dumping, Other)	Multiple response
	Biodiversity conservation practices (Agroforestry, Pollinator habitats, Soil cover crops)	Multiple response
Harvesting GAPs	Harvesting method (Hand-picking, Pole with basket, Other)	Categorical
	Harvesting timing (Mature, Immature, Overripe)	Categorical
	Use of clean harvesting tools	Yes/No
Post-Harvest GAPs	Post-harvest handling practices (Proper storage, Washing, Use of crates, Sorting, None, Other)	Multiple response
	Proper disposal of waste	Yes/No

	Compliance with pesticide withdrawal period (REI/PHI)	Yes/No
	Record keeping practices (Harvest records, Hygiene, Input logs, etc.)	Multiple response
	Training received on GAP and Post-harvest management	Yes/No

Appendix 5: Variables on Share of Harvest Exported

Variable	Questionnaire Section/Item	Measurement
Main market outlet	5.1 Main Market Outlet (Local Market, Export, Marketing Agents, Processor, Other)	Categorical – helps identify if farmer sells to export markets
Total harvest	4.2 Total Harvest Last Season (kg) and 4.5 Total Harvest This Season (kg)	Continuous (kg)
Quantity sold to export market	Not directly asked as quantity, but can be inferred from 5.1 Main Market Outlet combined with sales records if farmer mainly sells to export.	
Share of harvest exported	Derived variable = (Quantity sold to export market ÷ Total harvest) × 100	Computed percentage
Grade 1 produce proportion	5.4 What proportion of your harvest did you sell as Grade 1 last season (%)? and 5.8 …this season (%)	% share (proxy for export suitability, since only Grade 1 qualifies for export)