UNIVERSIDADE
EDUARDO
MONDLANE

FACULTY OF AGRONOMY AND FORESTRY ENGINEERING

DEPARTMENT OF ECONOMICS AND AGRICULTURAL DEVELOPMENT

Adaptation Strategies to the Impacts of Climate Change: Smallholder Farmers' Decision-Making on Climate-Smart Practices Adoption

By

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Reg No.: 20235541

A Dissertation Submitted in Partial Fulfilment of the Requirements for the Degree of Master of Science in Climate Change in Agrarian Systems.

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Maputo, 2026.

TABLE OF CONTENTS

ETHICAL DECLARATION

We the undersigned, hereby declare that the research study entitled **"Adaptation Strategies to the Impacts of Climate Change: Smallholder Farmers' Decision-Making on Climate-Smart Technologies Adoption"** was conducted for academic purposes as part of the requirements for the Master of Climate Change in Agrarian (Food) Systems at Eduardo Mondlane University. The study aims to investigate smallholder farmers' decision-making processes regarding the adoption of climate-smart agricultural practices as an adaptation strategy to the impact of climate change. The research assessed farmers' knowledge, perceptions, and factors influencing adoption of climate-smart technologies.

We confirm that data collection took place among smallholder farmers in Zavala District, Inhambane Province, Mozambique between August and mid-September 2025. We further confirm that:

- Participation of respondents was voluntary and informed about the purpose of the research prior to data collection.
- Participants had the right not to participate or withdraw at any stage without any consequence.
- All information obtained during the study treated with strict confidentiality and used solely for academic research purposes.
- No personal identifying information disclosed in any thesis, report or publication.
- The research adhered to accepted ethical standards, governing research involving human participants.
- The supervisor provided academic guidance to ensure that the research process complied with institutional research ethics requirements.

Student:

Signature________________________ **Date** 24/04/2026

Supervisor:

Signature________________________ **Date** 24/04/2026

DECLARATION OF ORIGINALITY

I Calvince Andele Ogutu, hereby declare that this thesis is my original work and has not been submitted for any degree or examination at any other institution. All sources of information have been duly acknowledge

Signature______________________ **Date** 24/04/2026

Andele O. Calvince

DEDICATION

I dedicate this thesis to smallholder farmers of Zavala District, Mozambique, whose resilience and willingness to share their experiences made this research possible. I submit that may this work contribute to improving their livelihoods and agricultural sustainability.

ACKNOWLEDGEMENT

This research would not have been possible without the generous cooperation of the 400 smallholder farmers in Zavala district who shared their time, knowledge, and experiences. Their willingness to participate in this study and their openness in discussing their farming practices and challenges are deeply appreciated.

I extend my sincere gratitude to the district agricultural office SDAE of Zavala for their invaluable support in facilitating access to communities, providing rosters, and offering insight into the local agricultural context.

I am grateful to team of extension officer (enumerators) who worked tirelessly under challenging field conditions to collect-high quality data. Their dedication, professionalism, and commitment to ethical research practices are commendable.

Special thanks to center of Excellence in Agri-Food Systems and Nutrition for the funds, Eduardo Mondlane University fraternity for providing institutional support and ethical approval for this research. The guidance and mentorship received from my supervisor and faculty members throughout the research process has been insightful.

I thank my family for their patience, understanding, and unwavering support throughout this endeavor

Finally, I thank God for enabling me to undertake the entire study thus far.

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
CI	Confidence Interval
DF	Degree of Freedom
CSA	Climate-Smart Agriculture
IPCC	Intergovernmental Panel on Climate Convention
FAO	Food and Agricultural Organization
IPM	Integrated Pest Management
OR	Odds Ratio
SD	Standard Deviation
SPSS	Statistical Package for the Social Sciences
SSA	Sub-Saharan Africa
VIF	Variance Inflation Factor
ICT	Information Communication Technology
GDP	Gross Domestic Product
DNA	Deoxyribonucleic Acid
CARE	Cooperative for Assistance and Relief Everywhere
CGIAR	Consultative Group on International Agricultural Research
ROC	Receiver Operating Characteristic
CIAT	International Centre for Tropical Agriculture
DoI	Diffusion of Innovation
SDAE	District Services for Economic Activities
MZN	Mozambican Meticais
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ITIKI	Information Technology and Indigenous Knowledge with Intelligence
GIS	Geographic Information Systems.
IoT	Internet of Things
ML	Machine Learning
AI	Artificial Intelligence
PROSPERO	International Prospective Register of Systematic Reviews
AGRICULTURE 4.0	Fourth Agricultural Revolution Applying Digital Technologies
CHIRPS	Climate Hazards Group Infra-Red Precipitation with Station Data
TAMSAT	Tropical Applications of Meteorology using Satellite Data

SAR	Synthetic Aperture Radar
LoRaWAN	Long Range Wide Area Network
SMS	Short Message Services
USSD	Unstructured Supplementary Service Data
ROBVIS	Risk of Bias Visualization
GSMA	Global System for Mobile Communication
PNISA	National Agricultural Investment Plan
KMO Measure	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.

ABSTRACT

Climate change severely threatens stallholder agriculture in Mozambique, where frequent droughts, floods, and cyclones undermine food security. Climate-smart agriculture (CSA) offers resilience-enhancing practices, yet despite decades of promotion, adoption among smallholders remain low, limiting climate adaptation. This thesis investigates farmers' perceptions of CSA practices and determinants of adoption, and synthesizes evidence on how digital agricultural technologies influence CSA decision-making. The study comprises a cross-sectional survey of 400 smallholder farmers in Zavala district, Mozambique, and a systematic review of 82 studies across sub-Saharan Africa. Results show that awareness of 13 CSA practices ranged from 47-100%. Three awareness-knowledge patterns emerged–awareness exceeding knowledge (rainwater harvesting, 81% awareness vs. 39% knowledge), knowledge exceeding awareness (improved varieties, 67% knowledge vs. 47% awareness), and aligned awareness and knowledge patterns for eight practices. Understanding of CSA principles lagged considerably ($r = 0.151$) with knowledge. Perceived compatibility ($\beta = 0.342$) and trialability ($\beta = 0.418$) were the strongest adoption drivers. The systematic review identified three complementary pathways through which digital technologies influence perceptions: real-time information provision, predictive analytics and integrated indigenous-scientific systems. Education was the strongest predictor of awareness-knowledge pattern: secondary-educated farmers knew nearly triple the practices of primary-only farmers (11.60 vs 6.82, $p < 0.001$). Women outperformed men on awareness (11.34 vs 7.47), knowledge (10.21 vs 6.82) and principles (9.45 vs 6.24) all at $p < 0.001$. Multinomial logistic regression showed that age (OR = 0.391), male gender (OR = 0.068), farming experience (OR = 1.322), and cooperative membership ($p < 0.026$) significantly differentiated adoption levels. Linear regression explained 83% of variance in awareness, 87% in knowledge but only 7.6% in understanding of principles. Systematic review identified interconnected infrastructural, economic, institutional, and gender as barriers to adoption. These findings imply that extension should shift from awareness campaigns to principle-based participatory training, align terminologies with farmers language, invest in secondary education, leverage women as peer educators, and address structural barriers like infrastructural, credit, and land rights. Digital technologies require simultaneous investment in enabling environments to scale, and adoption depends more on deep understanding and compatibility than simple awareness.

Keywords: Climate-Smart Agriculture, digital agricultural technology adoption, decision-making, smallholder farmer, Mozambique.

CHAPTER I: INTRODUCTION

1.1 Background and context

Sub-Saharan Africa (SSA) suffers the grave impacts of climate change despite being a minimal contributor of global greenhouse gas emission, (IPCC, 2022). The region has rapidly warmed than the rest of the world, and by 2050, temperatures are expected to rise by 1.5°C to 2.5°C. the regions agriculture, employing over 60% of the workforce, contributing to 30% GDP in some SSA economies is primarily rain-fed and extremely vulnerable to harsh weather events – temperature increase, and rainfall variations (Zeufack et al., 2021)

Mozambique, is one of the most climate-vulnerable countries in the world because of its long coastline, reliance on agriculture for 25% of its GDP and 80% of workforce (FAO, 2007; PNISA, 2017). Since 1980, the nation has seen more than 50 major climate-related disasters, such as droughts, floods, and cyclones. The country has experienced frequent climate-related disasters since 1980, including cyclones, floods, and droughts. About 1.5 million people were impacted by El Nino-induces drought that lasted from one year, between 2015 and 2016, and decreased national crop production by 15% (FAO, 2007; PNISA, 2017). More recently, agricultural systems in the central and northern provinces were severely devastated by cyclone Idai and Kenneth that occurred in 2019 (FAO, 2019). Over the past thirty years, farmers in southern Mozambique have faced increased unpredictable rainfall patterns, prolonged dry spells, and frequent droughts (Zita et al., 2025). As a result, crop yields have decreased, food security compromised, and rural livelihood weakened by these climatic stressors. The region's predominant sandy soils that cannot hold water and are nutrient poor exacerbates vulnerability particularly, to rainfall variabilities (Pereira & Esteves da Silva, 2024).

In response to these challenges, international development organizations and national agriculture extension services have promoted climate-smart agriculture (CSA) as a suit of practices designed to sustainably increase productivity, enhance resilience to climate shocks, and reduce greenhouse gas emissions where possible (Lipper et al., 2014). The CSA framework developed by the Food and Agricultural Organization (FAO), rests on three pillars: (1) sustainably increasing agricultural productivity and incomes, (2) adapting and building resilience to climate change, and (3) reducing greenhouse gas emission where feasibly (FAO, 2024). In southern Mozambique several government, non-governmental and community-based organizations have promoted a number of CSA technologies including drought-resistant crop varieties, conservation tillage, agroforestry, rainwater harvesting, integrated pest management (IPM), intercropping, cover cropping, Biofertilizers soil fertility management, and water efficient irrigating among others (CIAT; World Bank, 2017). These practices have demonstrated potential to increase yields ranging from 20–50% under certain conditions (Thierfelder et al., 2013; Oduor et al., 2023).

Despite sustained promotion efforts spanning over a decade, adoption rates among smallholder farmers remain disappointingly low, with many practices reaching only a majority of farming households (Araya et al., 2024). In Mozambique, adoption rates for CSA practices are relatively low; 44.6% adopt one or more conservation agriculture practices, yet most farmers still lag in adopting all components of CSA practices. Literature indicates that adoption of improved vegetable, maize and bean varieties is still below 20% (Nova & Rosário, 2022). This persistent low adoption represents a critical puzzle for agricultural development (Pretty et al., 2011).

Parallel to CSA development, advancements in digital technology have opened new frontiers for agricultural decision-making (Mollel et al., 2025; McFadden et al., 2022). Technologies such as remote sensing, geographic information systems (GIS), Internet of Things (IoT) sensors, and artificial intelligence (AI) offer potential to enhance smallholder farmers' adaptive capacity by providing real-time information, predictive analytics, and optimized scheduling (Basso & Antle, 2020; Mhlanga & Ndhlovu, 2023). However, evidence on how these digital tools practically influence CSA adoption in SSA remains fragmented and context dependent.

1.2 Problem statement

The persistent low adoption of CSA technologies in Mozambique and across SSA persists despite substantial investment in technology development, dissemination, and extension. Understanding why farmers adopt or reject CSA practices requires moving beyond simplistic economic models to examine the perceptual, social, cognitive , and structural factors that shape farmers' decisions (Doss, 2017). Rogers' Diffusion of Innovation (DOI) theory has provided the dominant framework for understanding adoption in agriculture Rogers, (2003), proposing five perceived attributes – relative advantage, compatibility, complexity, trialability, and observability influencing adoption decisions. However, empirical applications of DOI in SSA smallholder contexts have produced inconsistent findings, raising questions about the cultural and contextual validity of these dimensions (Glover et al., 2019; van Hulst et al., 2020).

Although climate-smart agriculture has been widely promoted as an adaptation strategy to climate change, evidence suggests that adoption among smallholder farmers in Mozambique remains inadequate. Come, (2021) found that adoption of several improved agricultural technologies remain below 20% while conservation agriculture adoption reached 39.9%, highlighting persistent gaps in the uptake of climate-resilient farming practices. At the same time, the integrated agricultural survey Ministério da Agricultura e Desenvolvimento Rural (MADER, 2021) reported that only 6.9% of farmers had access to extension services, limiting opportunities for knowledge transfer and technical support. These findings suggests that barriers to CSA adoption extend beyond the availability of technologies and may be linked to farmers' awareness, knowledge, and decision-making processes.

Furthermore, existing research has documented significant disparities in adoption by gender, education, age, and social capital (Doss & Morris, 2001; Fisher & Carr, 2015). Women famers cross SSA consistently demonstrate lower adoption rates than men, attributed to differential access to land, credit, extension and decision-making power (Peterman et al, 2010). Education has emerged as consistent positive predictor of adoption while relationship between age and adoption shows patterns that are more complex (Knowler & Bradshaw, 2007). Recent empirical work in SSA confirms these patterns, though with important contextual nuance (Qange et al., 2025; Yusuf et al., 2024). Social networks and peer effects have been identified as crucial in pathways for information diffusion, yet the mechanisms remain poorly understood (Karim & Thiel, 2026).

Beyond these farm-level determinants, digital agricultural technologies promise to enhance CSA adoption by reducing uncertainty and improving information access. However, significant gaps remain in understanding how remote sensing, GIS, and IoT technologies practically influence smallholder farmers' CSA adoption decisions in SSA (Jellason et al., 2021; Nyaga et al., 2021). Existing research tends to examine individual technologies in isolation, fails to synthesize how different digital tools collectively shape decision-making processes, and gives limited attention to the interconnected nature of infrastructural, economic, institutional, and gender barriers (Choruma et al., 2024; Mhlanga & Ndhlovu, 2023). Moreover, the persistent "pilot-to-scale" gap where successful demonstrations fail to achieve widespread adoption requires systematic investigation (Rurii & Nzengya Daniel, 2026; Appiah et al., 2025).

This study addresses these gaps through two complementary investigations: (1) an empirical study of CSA adoption determinants among 400 smallholder farmers in Zavala District, Mozambique, and (2) a systematic review of digital agriculture technologies' influence on CSA decision-making among smallholder farmers across sub-Saharan Africa.

1.3 Research objectives

1.3.1 General objective

This study aims to analyze the adoption of climate-smart agriculture (CSA) technologies among smallholder farmers within a multidimensional framework of behavioral, institutional and livelihood factors.

1.3.2 Specific objectives

i. Assess farmers’ awareness, knowledge, and understanding of CSA technologies.
ii. Evaluate how perceptions of these technologies based on innovation attributes influence adoption.
iii. Examines how institutional factors and livelihood assets shape CSA adoption.

For Systematic review:

iv. To synthesize the role of digital technologies in influencing CSA-related decision-making.

1.4 Research questions

Four research questions guide the inquiry:

i. What is the level of smallholder farmers’ awareness, knowledge, and understanding of CSA?
ii. How do farmers’ perceptions of CSA technologies influence their adoption decisions?
iii. How do institutional factors and livelihood assets affect CSA adoption?
iv. How do digital agriculture technologies influence farmers decision-making regarding CSA practices?

1.5 Research hypotheses

The following null (H_0) and (H_1) hypotheses were formulated to guide the statistical analyses, corresponding to three specific objectives of the study.

Hypotheses related to specific objective 1 (awareness and knowledge of CSA technologies)

H1a: (Differences between awareness and knowledge levels across 13 CSA practices)

- **H_0:** There is no statistically significant difference between awareness and knowledge levels across the 13 CSA practices
- **H_1**: There is a statistically significant difference between awareness levels and knowledge levels across the 13 CSA practices

***Test**: Paired t-tests*

H1b: (Gender differences)

- **H_0:** There is no statistically significant difference between male and female farmers in awareness, knowledge, and understanding of principles
- **H_1:** Female farmers have significantly higher awareness, knowledge and understanding of principles score compared to male farmers (tested using independent sample t-tests and Man-Whitney U tests).

Test: *Independent sample t-tests and Mann-Whitney U tests*

H1c: (Education level association)

- **H_0:** Education level is not associated with awareness, knowledge, or understanding of principles scores (mean across education levels are equal)
- **H_1:** Education level is positively associated with higher awareness, knowledge, and understanding of principles scores

Test: *One-way ANOVA with Turkey HSD post-hoc comparisons.*

H1d (Correlations among awareness, knowledge, and principles)

- **H_0:** There is no significant correlation between awareness and knowledge, and no significant correlation between awareness/knowledge and understanding of principles (all correlate at 0)
- **H_1:** Awareness and knowledge are strongly correlated while awareness /knowledge are weakly correlated with understanding of principles.

Test: *Pearson and Spearman correlation coefficient*

Hypotheses related to specific objective 2 (perceptions of CSA technologies)

H2a: (Dimensionality of Rogers' five attributes)

- **H_0:** Rogers' five perceived attributes are not empirically distinguishable in the Zavala smallholder context (collapse into a single factor)
- **H_1:** Rogers' five perceived attributes are empirically distinguishable dimensions in Zavala smallholder context (load onto two or more factors)

Test: *Principal component factor analysis (KMO, Bartlett's test, eigenvalue >1 criterion).*

H2b: (Compatibility and trialability as strong predictors)

- **H_0:** Perceived compatibility and trialability are not the strongest predictors of adoption progression (their regression coefficients are not significantly larger than those of other attributes)
- **H_1:** perceived compatibility and trialability are the strongest predictors of adoption progress compared to relative advantage, complexity (reversed), and observability

Test: *Multinomial logistic regression and linear regression models (comparison of standardized beta coefficients).*

H2c: (Perception score and adoption level)

- **H_0:** There is no significant difference in composite perception scores across low, moderate, and high adoption levels
- **H_1:** higher perception scores associated with higher adoption levels

Test: *ANOVA (F-test) and regression analysis.*

Hypotheses related to specific objective 3 (institutional factors and livelihood assets)

H3a: (Cooperative membership and adoption)

- **H_0:** Cooperative membership does not significantly increase the odds of being in higher adoption categories (moderate or high) compared to non-members
- **H_1:** Cooperative membership significantly increases the odds of being in higher adoption categories (moderate or high) compared to non-members

Test: *Multinomial logistic regression (odds ratios).*

H3b: (Extension contact frequency)

- **H_0:** Extension contact frequency is not positively associated with awareness, knowledge, or adoption levels (coefficient 0 or negative)
- **H_1:** Extension contact frequency is positively associated with awareness, knowledge, and adoption levels

Test: *Linear (awareness/knowledge) and logistic regression (adoption levels).*

H3c: (Age and farming experience)

- **H_0:** age is not negatively associated with adoption, and farming experience shows no positive association with adoption

- **H_1**: Age is negatively associated with adoption while farming experience shows a positive but weaker association

Test: *Regression analysis with comparison of beta coefficients.*

H3d: (Combined variance explained by demographic, institutional, and perceptual factors)

- **H_0**: the combination of demographic, institutional, and perceptual factors explain no variance in adoption outcome ($R^2 = 0$ or not significantly > 0)
- **H_1**: the combination of demographic, institutional, and perceptual factors explains significant variance in adoption outcomes ($R > 0$, F-test $p < 0.05$)

Test: *R^2 with F-tests for model significance*

1.6 Justification and significance of the study

This study makes several important contributions:

Theoretically, it tests the applicability of Rogers' DoI framework in Mozambican smallholder farming context, providing evidence on whether the five perceived attributes are empirically distinct or culturally bound. The results challenge conventional application of DoI and suggests need for context-specific measurements approaches. The systematic review develops an integrated socio-technical framework that bridges cognitive hierarchy (awareness → knowledge → principles) with technological pathways and enabling conditions, moving beyond simplistic adoption models.

Methodologically, the empirical study employs a three-level measurement framework (awareness, knowledge, principle) that captures distinct cognitive stages and composite measures to address terminology mismatch. The systematic review follows PRISMA guidelines and provides a replicable model for evidence synthesis in agricultural research.

Empirically, the study provides rare empirical evidence from Mozambique, a climate-vulnerable country with limited adoption research. The documentation of women's higher awareness and knowledge challenges conventional narratives. The systematic review synthesised eight-two (82) studies across fifteen (15) countries, offering the most comprehensive analysis to date of digital agriculture's influence on CSA adoption.

Practically, the study generates actionable recommendations for extension programing, policy development, and technology design – including prioritizing training on rainwater harvesting, leveraging women as peer educators, investing secondary education as agricultural policy, redesigning extension for low-literacy farmers, and addressing structural gender barriers.

1.8 Structure of the study

This dissertation is organized into seven chapters.

Chapter 1 (General introduction) introduces the study, presenting the background, problem statement, research questions, objectives, justification and significance, methodological overview and structure. This chapter establishes the rationale for the research and provides an overview of the study's contributions. **Chapter 2 (Literature review)** presents the theoretical framework (Diffusion of Innovation and Bloom's revised taxonomy), key concepts and definitions, critical synthesis of existing studies on CSA awareness, knowledge, gender, education institutional factors, perceptions, and local knowledge identification of knowledge gaps, and a conceptual model integrating cognitive progression with enabling conditions. This chapter situates the study within existing research and identifies gaps that the study addresses. **Chapter 3 (Methodological framework)** describes the overall research design, study area (Zavala District and broader SSA context), population and sampling procedures, data collection methods and instruments, data analysis techniques, ethical considerations and study limitations. **Chapter 4 (Research paper 1)** presents the empirical study "Adoption Strategies to the Impact of Climate Change: Smallholder Farmers' Decision-Making on Climate-Smart Technologies Adoption" including an introductory linking paragraph and statement of authorship contribution. **Chapter 5 (Research paper 2)** presents the systematic review "Mediated Influence of Digital Agricultural Technologies on Climate-Smart Agriculture Decisions among Smallholder Farmers in Sub-Saharan Africa: A Systematic Review" including a statement of authorship contribution. **Chapter 6 (Integrative discussion)** synthesizes findings across both papers, compares with existing literature, discusses theoretical and practical implications, and acknowledges limitations. **Chapter 7 (Conclusion and recommendation)** provides recommendations for future research, and presents a general conclusion summarizing major findings, contributions to knowledge and final remarks.

CHAPTER II: LITERATURE REVIEW

2.1 Theoretical framework

This thesis integrates two complementary theoretical frameworks: Rogers' Diffusion of Innovation (DOI) theory and Bloom's revised taxonomy of educational objectives.

2.1.1 Diffusion of Innovation Theory

Rogers Diffusion of Innovation theory, first published in 1962 and refined across five editions, remains the most widely cited framework for understanding technology adoption across multiple domains, including agriculture, public health and information technology (Rogers, 2003). Rogers defines diffusion as the means by which a new idea, technology, or practice is gradually communicated and adopted among members of a social system over time. The spread of innovation depends on communication channels, social interactions, and perceived usefulness of innovation and characteristics of potential adopters.

Rogers conceptualizes adoption as a process occurring over time through five sequential stages: **(i) the knowledge stage** where an individual learns of the innovation's existence and gains some understanding of its functioning, **(ii) the persuasion stage** in which an individual forms a favorable or unfavorable attitude towards the innovation. **(iii) the decision stage** have the farmer engages in activities that lead to a choice to adopt or reject the innovation; **(iv) the implementation stage**, where the farmer puts the innovation into use on a small scale; and **(v) the confirmation stage,** where the farmer seeks reinforcement for the adoption decision and may reverse it if exposed to conflicting messages.

Within this framework, five perceived characteristics of innovation determine the rate of adoption (Rogers, 2003). **Relative advantage** refers to the degree to which an innovation is perceived as better than the idea it superseded. In agricultural contexts, this typically encompasses yield increases, cost reductions, labor savings, or income improvements to enhance resilience and improve food security. Innovations perceived as offering greater relative advantage are adopted more rapidly. **Compatibility** refers to the degree to which an innovations, is perceived as consistent with existing values, past experiences, and needs. **Complexity** refers to the degree that an innovation is perceived as difficult to understand and use. **Trialability** is the degree that an innovation can be experimented with on a limited scale. **Observability** refers to the degree that the results of an innovation are visible to others. These attributes have been extensively validated in agricultural technology adoption research Finizola e Silva et al. (2024), though recent critiques question their dimensionality in smallholder contexts (Glover et al., 2019; van Hulst et al., 2020).

The study operationalizes Rogers' framework by focusing on the three critical stages that corresponds to the knowledge, persuasion, and confirmation stages of the adoption process. The awareness corresponds to Rogers' knowledge stage, where farmers learn of CSA practices and gain basic understanding of their existence. The knowledge stage corresponds to the implementation stage, where farmers understand how to put practices into use. The understanding principles stage corresponds to the confirmation stage, where farmers develop deep understanding that enables sustained use and adoption.

2.1.2 Bloom's revised taxonomy and the knowledge hierarchy

Understanding farmers' cognition regarding agricultural innovations is complex and multi-dimensional. Drawing on educational psychology, Krathwohl (2002) and Anderson & Krathwohl (2001) developed Bloom's revised taxonomy, which classifies learning objectives along two dimensions: the cognitive process dimension (what learners do) and the knowledge dimension (type of knowledge). The knowledge dimension includes factual knowledge (basic elements), conceptual knowledge (interrelationships among basic elements), procedural knowledge (how to do something), and metacognitive knowledge (awareness of one's own cognition).

This operationalizes farmer understanding at distinct levels that correspond to this taxonomy: (1) Awareness – in this dimension, a farmer has heard of the CSA practice and knows its existence; this represents declarative knowledge as its most basic level (Leslie, 2016). Awareness is necessary but not sufficient for adoption; Ogunyiola et al. (2022) emphasize that awareness alone does not guarantee adoption, as farmers' local knowledge systems may interact with introduced practice in a complex manner. (2) Knowledge – the farmer understands how to implement the practice, representing procedural knowledge or the ability to perform the practice (Ryle & Town, 1994). Farmers at this level can potentially apply the practice on their farms, though they may face resource, structural or institutional hurdles. (3) Understanding of principles – a level where farmers comprehend the underlying scientific principles and concepts. This represents conceptual knowledge – understanding why the practice works (Krathwohl, 2002; Rogers, 2003). Farmers at this level can adapt practices to their specific contexts and troubleshoot problems independently, critical for sustained adoption and innovation (Glendenning, 2010). Achieving principle-level understanding requires more intensive, participatory approaches such as farmer field schools and long-term engagements (Moumeni-Helali & Ahmadpour, 2013).

These three – level framework provides a more nuanced assessment of farmer cognition than simple binary measures of awareness or adoption commonly used in agricultural research (Evenson & Gollin, 2003; Udry et al., 2024; Evenson & Gollin, 2003).

2.1.3 Integration: A unified framework for CSA adoption

This thesis integrates DOI theory and Bloom's taxonomy to propose a unified framework in which (i) awareness corresponds to Rogers' knowledge stage (exposure and basic understanding); (ii) knowledge corresponds to the implementation stage (procedural competence), and (iii) understanding of principles corresponds to the persuasion and confirmation stages (deep comprehension enabling sustained adoption). The framework further proposes that farmers' progression across these stages is influenced by four interrelated categories of determinants: farmer characteristics (age, education, experience), farm characteristics (size, tenure, soil quality), institutional factors (extension, credit, cooperatives, markets), and perception factors (perceived attributes, risk perception). Digital agricultural technologies are positioned as moderators that can accelerate progression through these stages by providing real-time information (enhancing awareness), predictive analytics (building procedural knowledge), and integrated indigenous-scientific systems (developing conceptual understanding).

2.2 Definition of key terms:

Climate-Smart Agriculture: Climate-smart agriculture is defined by the Food and agriculture Organization FAO (2013) as an approach that aims at transforming agricultural systems to simultaneously enhance productivity, strengthen resilience to climate variability, and reduce greenhouse gas emissions where possible. The CSA framework emphasizes context-specific strategies that improve food security while supporting environmental sustainability and adaptation to climate change (Lipper et al., 2014).

Awareness: Awareness refers to the condition in which an individual is informed about the existence of a particular idea, technology or practice. In this study, awareness describes whether a farmer has previously encountered or heard about a specific climate-smart agriculture (CSA) practice. At this stage, the farmer recognizes the practice but may not yet be able to apply it or explain how it functions. Awareness represents an initial level of cognitive engagement and corresponds to basic declarative knowledge, where an individual knows that something exits but does not necessarily understands its application or underlying logic (Krathwohl, 2002). Awareness therefore considered a necessary first step in the innovation process, as farmers must first be exposed to a practice before they can evaluate or drop it (Ogunyiola et al., 2022; Ogisi & Begho, 2023).

Knowledge: Knowledge is the practical understanding required to apply a practice effectively in real-life farming conditions (Ryle & Town, 1994). Within this study, knowledge indicates that a farmer knows how to implement a CSA practice, including the skills, procedures, and management requirements involved. This form of knowledge reflects procedural competence, meaning the farmer is capable of carrying out the steps necessary to use the practice appropriately. In agricultural contexts, such knowledge may include understanding of timing of operations, selection of inputs, required tools, and management strategies (Meijer et al., 2015). Knowledge is often developed through extension services, farmer-training programs, demonstrations, and experiential learning, and it plays a critical role in enabling farmers to move beyond awareness toward actual use of agricultural innovations.

Understanding principles: Understanding principles refers to a deeper level of understanding of comprehension concerning the scientific, ecological, or agronomic mechanisms that explain why a practice works. In the context of CSA, this involves recognizing the cause-effect relationships that make practices beneficial, such as how soil cover improves moisture retention, how crop diversity enhances resilience, or how to improved varieties responds to climate stress. This level of understanding represents conceptual knowledge because it allows farmers to interpret relationships on different farming components and adapt practices to their local conditions (Krathwohl, 2002). Farmers who understand principles are more likely to modify practices appropriately, solving problems independently, and apply innovations flexibly in response to changing environmental conditions. This enhances sustained adoption, and thus becoming co-creators of innovators and knowledge providers (Glendenning, 2010).

Adoption is defined as the decision by a farmer to consistently apply agricultural innovation over time (Rogers, 2003). In farming contexts, adoption has been traditionally measured as a simple yes-or-no outcome indicating whether a farmer uses a practice. However, this study views adoption as a dynamic and gradual process that develops as farmers build familiarity, competence, and confidence in a practice. Rather than representing a single event, adoption is understood as a process that unfolds through multiple stages of learning and evaluation, reflecting progressive engagement with agricultural innovations. This perspective is consistent with innovation-decision framework proposed by Everett Rogers. This conceptualization acknowledges that adoption is not a single decision point but a journey that requires building different types of knowledge at different stages.

Adoption progression: Adoption progression refers to the cumulative advancement of farmers through successive levels of familiarity with CSA practice, from initial exposure to deeper comprehension. This concept captures the extent to which the farmers have developed understanding of individual practices, with which they have engaged. Adoption progression therefore reflects the overall degree of cognitive involvement in climate-smart farming approaches. Considering progression as a continuum enables recognition that farmers may be at different stages of learning for different practices and that meaningful adoption often develops gradually through experience and repeated exposure. Adoption progression is conceptualized as a composite measure that reflects the farmer's overall cognitive engagement with CSA practice(s).

Digital agriculture technologies: technological tools including remote sensing (satellite imagery, drones-based sensors), geographic information systems (GIS) for spatial analysis, internet of things (IoT) sensors (soil moisture, weather stations), artificial intelligence/machine learning for predictive analytics and digital advisory platforms (mobile apps, SMS services, decision support tools). These technologies support decision-making through real-time information provision, risk assessment, and optimized timing.

S**ocial capital:** refers to the social relationships, shared norms, and levels of trust that enables individual to exchange information and collaborate effectively. In agricultural setting, social capital influences how farmers access knowledge, learn from one another, and collectively responds to environmental challenges, in this study, social capital is operationalized through advice-sharing behavior, especially whether a farmer exchanges agricultural information with other farmers. Strong social networks can enhance learning opportunities, facilitate experimentation, and increase the likelihood that a farmer engages with new agricultural practice.

2.3 Critical synthesis of existing studies

2.3.1 Studies on knowledge and awareness of climate-smart agriculture practices

The relationship between awareness, knowledge and adoption of climate-smart agriculture (CSA) remains one of the most debated issues in agricultural innovation research. While enormous studies identify awareness as a prerequisite for adoption, there is limited consensus regarding whether awareness alone is sufficient to stimulate behavioral change. Most adoption studies implicitly assume a linear progression from awareness to knowledge and ultimately adoption, yet empirical evidence suggests that this relationship is considerably more complex. Early adoption studies generally report positive association between awareness and technology uptake. For example, Kato et al. (2011), Kpadonou (2017) and Teklewold et al. (2019) found that farmers who were aware of agricultural innovations were most likely to adopt them. However, these studies primarily measure awareness as simple exposure to information and did not assess whether farmers possessed sufficient technical understanding to implement the practices effectively. Consequently, their findings provide limited insight into the mechanisms through which awareness translates into adoption

Several scholars have challenged the assumption that awareness automatically leads to adoption. Glendenning (2010) argued that awareness represents only the initial stage of learning and must be complemented by procedural and conceptual knowledge before farmers can make informed adoption decision. Similarly, Miehe (2025) demonstrated that increased information does not necessarily increase adoption. Rather, correcting inaccurate beliefs about agricultural innovations reduce farmers' intentions to adopt, suggesting that adoption decision depends on the quality and credibility of information rather than merely its availability. These finding challenge the conventional diffusion models that equate information dissemination with behavioral change.

A major limitation of the existing literature is the tendency to treat knowledge as a unidimensional construct. Most studies measure knowledge using aggregate scores without distinguishing between factual knowledge (awareness of practice), procedural knowledge (understanding how to implement it), and conceptual knowledge (understanding why it works). This methodological simplification obscures important differences in farmer' learning process and limits understanding of how knowledge influences adoption intensity. Consequently, studies reporting positive relationships between knowledge and adoption often fail to explain which forms of knowledge are the most influential.

Th literature also presents conflicting evidence regarding the relative importance of awareness and knowledge. While Partey et al. (2018) reports high levels of CSA awareness among farmers in Ghana, adoption rates remained considerably lower than awareness levels, similar discrepancies have been documented across sub-Saharan Africa, where farmers often demonstrate familiarity with technologies but fail to implement them consistently. Such findings suggest that awareness may be necessary but insufficient for adoption. Instead, adoption appears to require deeper forms of understanding that enable farmers to evaluate risks, benefits, and compatibility with existing farming systems.

Another limitation concern the dominant reliance on cross-sectional survey designs. Most studies infer casual relationships between awareness, knowledge, and adoption using single-period observations, making it difficult to determine whether knowledge leads to adoption or whether adoption itself enhances knowledge through experiential learning. This raises concerns about endogeneity that remain largely unaddressed in the CSA adoption literature. Furthermore, existing studies have focused predominantly on whether farmers adopt or do not adopt innovations, paying limited attention to differences in adoption intensity. Farmers classified as adopters may vary substantially in the extent to which they implement, sustain, and integrate technologies into their farming systems. Consequently, binary adoption measures may conceal important variation in learning and behavioral change.

The reviewed literature therefore reveals three important gaps. First, there is sufficient differentiation between awareness, procedural knowledge, and conceptual understanding. Second, limited attention has been given to how these forms of knowledge influence different levels of adoption intensity. Third, empirical evidence from Mozambique remains scarce despite the country’s high vulnerability to climate change and relatively low levels of conceptualization o learning that examines awareness, knowledge, and understanding of CSA principles as distinct but related dimensions influencing adoption behavior

2.3.2 Studies on gender and education in adoption

Gender and education are widely recognized as important determinant of agricultural technology adoption; however, the empirical evidence remain inconsistent and context-dependent. Earlier adoption studies generally reported that male farmers were more likely to adopt agricultural innovation due to their greater access to land credit extension services, and decision-making authority (Doss, 2017). This perspective aligns with resource-based theories, which argue that adoption is primarily constrained by access to productive assets. However, more recent studies have challenged this assumption by demonstrating that female farmers often exhibit equal or higher adoption rates when structural barriers are controlled for (Teklewold et al., 2019; Ndiritu et al., 2014; Tabe-Ojong et al., 2024).

The conflicting findings suggest that gender itself may not directly influence adoption. Rather gender often serves as a proxy for unequal access to information, resources, and institutional support. Consequently, studies that report significant gender differences without controlling for these factors may overestimate the independent effect of gender (Teklewold et al., 2013; Kassie et al., 2015; Mwangi & Kariuki, 2015). Furthermore, many adoption studies conceptualize gender as binary variable, ignoring intra-household decision-making dynamics and the increasingly important role of women in climate adaptation. This simplification limits understanding of how gender relations influence awareness, knowledge acquisition, and adoption decision.

The evidence regarding education is more consistent. Numerous studies report positive relationship between educational attainment and adoption of climate-smart agricultural practices (Kpadonou et al., 2017; Araya et al., 2024). Education is believed to enhance information-processing capacity, risk assessment, and the ability to understand technical recommendations. Nevertheless, most studies assume that education directly influences adoption without examining the intervening learning processes through which education affects awareness and knowledge. This represents a significant theoretical limitation because education may influence adoption indirectly by enhancing farmers' capacity to acquire, interpret, and utilize information.

A further limitation is the dominance of cross-sectional studies that establish associations rather than causality. While education is constantly associated with adoption, it remains unclear whether educational attainment directly influences adoption Behaviour or whether education merely reflects broader socio-economic advantages. Consequently, the mechanisms linking education to awareness, knowledge and adoption remain poorly understood. The literature therefore lacks a comprehensive understanding of how gender and education influence different stages of learning and adoption. This study addresses this gap by examining their effects on awareness, knowledge and understanding of CSA principles and adoption intensity simultaneously.

2.3.3 Evidences on institutional factors and social networks

Institutional factors are among the most frequently cited determinants of agricultural technology adoption. Extension services, credit access, market participation, and cooperative membership are generally assumed to facilitate adoption by reducing information and resource constraints. Interestingly, despite widespread agreement regarding their importance, significant inconsistencies exist regarding the magnitude and mechanisms of their influence. For instance, extension services are often portrayed as the primary channel through which farmers acquire agricultural knowledge (Davis & Sulaiman, 2020). While numerous studies report positive association between extension contact and adoption, others have found weak or insignificant effects (Kansiime et al., 2022; Meijer et al., 2015). These inconsistencies may reflect differences in extension quality rather than extension availability. Most studies measure extension using simple contact indicators, which fail to capture the frequency, quality, relevance, and participatory nature of the extension interactions. This may lead to the existing evidences underestimating the complexity of extension influence.

Similarly, access to credit commonly associated with higher adoption rates because it enables investment in practices that require running upfront capital. However, empirical findings remain mixed. Some studies report strong positive effect, whereas others find limited influence after controlling for farm size and income. These inconsistencies suggest that credit alone may not guarantee adoption unless accompanied by information, technical support, and market opportunities. Research on cooperative membership and social networks generally report positive effects on adoption through information sharing and collective action. Nevertheless, most studies treat farmer organizations as homogeneous entities, overlooking substantial variation in organization effectiveness, governance, and service provision. Furthermore, social networks studies frequently assume that information shared within the networks is accurate and beneficial, despite evidence that misinformation can also spread through social interactions.

The literature also exhibits a strong outcome bias. Most studies evaluate institutional effectiveness based on the adoption outcomes without investigating how intuitions contribute to awareness creation, knowledge development, and conceptual understating. The result is that the pathways through which institutional support influences adoption remain poorly specified. This study addressed these limitation by examining how institutional factors influence multiple dimensions of learning and adoption rather than focusing solely on adoption outcomes.

2.3.4 Evidences on perception factors and Diffusion of Innovation

Rogers' Diffusion of Innovation (DOI) theory (Rogers, 2003) remains one of the most influential frameworks for explaining agricultural technology adoption. The theory proposes that adoption decisions are influenced by perceptions of relative advantage, compatibility, complexity, trialability, and observability. Although these attributes have received substantial empirical support, recent research increasingly question their universality and explanatory sufficiency. Among the five attributes, relative advantage and compatibility consistently emerge as th strongest predictors of adoption (Knowler & Bradshaw, 2007). Notwithstanding, findings regarding complexity, observability, and trialability are considerably less consistent. While some studies report significant effects, others find limited or no influence. These inconsistencies suggest that the importance of innovation attributes may vary according to context, technology type, and adoption stage.

A major limitation of DOI-based studies is their assumption that farmers evaluate innovation attributes independently. In practice, perception of relative advantage, compatibility, and complexity are often interrelated for example, a technology perceived as highly compatible may simultaneously be viewed as less complex. The failure to account for these interrelationships may lead to oversimplified explanations of adoption behavior. Another criticism concern the theory is limited consideration of structural constraints. DOI theory focuses primarily on individual perceptions while giving relatively little attention to institutional, economic, and social barriers. Thus, farmers may perceive an innovation positively, yet remain unable to adopt it because of financial or resource limitations. This limitation is particularly relevant in stallholder farming systems, characterised by significant resource constraints.

Furthermore, many studies assume that innovation attributes exert uniform effects across all adoption stages. Nonetheless, emerging evidence suggests that compatibility may be more important during initial stages of adoption while relative advantage may become increasingly important for sustained adoption. Despite these insights, relatively few studies explicitly investigate whether innovation attributes influence moderate and high adoption differently. This study contributes to the literature by examining the relative importance of perception attributes across different adoption levels rather than treating adoption as binary outcome.

2.3.5 Evidences on local knowledge, terminology and measurement challenges

The growing emphasis of climate-smart agriculture has generated considerable debate regarding the role of local knowledge and the measurement of adoption. While CSA is often promoted as scientifically grounded approach to climate change adaptation, critics argue that many interventions inadequately recognize indigenous knowledge systems that have supported adaptation for generations. Several studies emphasize the importance of integrating local knowledge into adoption strategies (Ogunyiola et al., 2022) however, much of the CSA literature continues to prioritize externally developed technologies and scientific expertise (FAO, 2025). Failure to incorporate local knowledge may undermine farmer ownership and limit long-term sustainability.

The literature also reveals substantial challenges regarding the conceptualization and measurement of adoption. Many studies classify farmers as adopters or non-adopter despite evidence that adoption is a dynamic and multidimensional process. Such binary classifications obscure differences in adoption intensity, duration, and quality of implementation. Measurement accuracy presents an additional concern. Studies such as Kosmowsk et al. (2018)

have demonstrated significant discrepancies between farmer-reported and objectively verified adoption rates. These findings raise concerns about the validity of self-reported adoption data widely used in agricultural research. Furthermore, there is limited consensus regarding how awareness, knowledge, and understanding of principles should be measured. Many studies employ simple knowledge indices without distinguishing between different forms of learning, thereby limiting theoretical precision and compatibility across studies. This study address these challenges by conceptualizing adoption as a multi-level outcome and distinguishing awareness, knowledge, and understanding of principle as separate dimensions of learning.

2.3.6 Studies on digital agriculture and CSA decision-making

Digital agriculture is increasingly promoted as a transformative solution for improving climate adaptation and agricultural decision-making. Mobile application, remote sensing, artificial intelligence, and internet of things technologies are expected to improve access to information, and strengthen resilience. Despite this optimism, the evidence regarding their effectiveness remain mixed and fragmented. Proponents argue that digital technologies improve access to climate information, reduce uncertainty, and enhance decision-making (Kuradusenge et al., 2014). Nevertheless, much of the existing evidences originate from pilot-to-study projects and controlled interventions, raising concerns about scalability and sustainability. Technologies that perform well under experimental conditions may face substantial implementation challenges in resource-constrained environments.

A significant limitation of the digital agriculture literature is its tendency towards technological determinism. Many studies assume that providing digital tools will automatically improve decision-making and adoption. However, evidence suggest that access to technology does not guarantee effective utilization. Factors such as digital literacy, affordability, infrastructure, trust and institutional support significantly influence technology use. Moreover, most studies focus on immediate outcomes such as information access, productivity, or adoption. Comparatively little attention has been given to understanding whether digital technologies contribute to deeper learning conceptual understanding and long-term behavourial change. This limitation is particularly important because sustainable adaptation requires more that access to information; it requires the capacity to interpret, evaluate, and apply that information effectively.

The literature also pays limited attention to the interaction between digital technologies and traditional knowledge systems. Recent studies suggest that digital solutions are most effective when they integrated with indigenous knowledge, social learning, and extension support rather than replacing them. Therefore, while digital technologies offer considerable potential for enhancing climate adaptation, their role in promoting awareness, knowledge understanding and adoption remains insufficiently understood. This study addresses this gap by incorporating digital information pathways into the broader learning and adoption framework.

2.4 Overall synthesis of research gaps

A critical review of literature reveals four shortcomings. First, most studies focus on adoption outcomes while paying insufficient attention to the learning process that precedes adoption. Second, awareness, knowledge, and understanding of principles are frequently treated as interchangeable concepts despite evidence that they represent distinct stages of learning. Third, existing studies rarely examine how determinants influence different levels of adoption intensity. Finally, limited empirical evidence exists in Mozambique, particularly regarding the interaction between human capital, institutional support, perception attributes, and learning processes in shaping CSA adoption. Consequently, the study proposes a more integrated framework that conceptualizes adoption as an outcome of a cumulative learning process involving awareness, knowledge, and understanding the principles of CSA. Examining how human assets, institutional factors, perception attributes and informational pathways influence each stage of learning and adoption is important for this study since it enables both theoretical and empirical contributions to climate-smart agriculture adoption literature.

2.5 Conceptual model

Drawing on the diffusion of innovation theory and empirical literature on agricultural technology adoption, this study develops a conceptual framework (Figure 2.1) that explains how farmers progress through multiple levels of understanding of CSA practices and how digital technologies can facilitate this progression.

Component 1: Determinants (influence factor):

Four categories shape farmers' ability to progress through cognitive stages: (i) Farmer characteristics (e.g. education, experience, and cognitive capacity) affect how quickly a farmer moves from awareness to knowledge and finally to understanding of principles associated with particular CSA practice(s). (ii) Farm characteristics (e.g. size, tenure, soil quality) determine if a farmer has the practical means to experiment and learn the CSA practice(s). (iii) Institutional factors (e.g. extension services, credit access, market access, cooperatives, government policies) facilitate progression by providing training and technical support. (iv) Perception factors (e.g. perceived attributes including relative advantage, compatibility, complexity, trialability, observability) if CSA practice is seen as too complex, a farmer may stay away at the awareness stage.

Component 2: Hierarchical stage of Understanding

Farmers progress through three cumulative stages: stage 1 – awareness (“I have heard about the CSA practice”); stage 2 – knowledge (“I know what the practice is and how to do it”); stage 3 – understanding of principles (“I understand how and why the practice works, including mechanisms, synergies, and trade-offs”). This mirrors Rogers’ 2003 innovation-decision process, where the awareness phase involves learning that an innovation exists and how it works (knowledge), while the persuasion phase involves forming a favourable or unfavourable attitude through deeper comprehension (understanding of principles).

Component 3: Digital technology pathways

Digital agriculture technologies influence this progression through three pathways: pathway 1 – real-time information provision (IoT sensors, remote sensing) enhancing awareness; pathway 2 – predictive analytics for risk assessment (AI/ML) building procedural knowledge; pathway 3 – timing guidance through optimized scheduling and early warning (integrated indigenous-scientific systems) developing conceptual understanding.

Component 4: adoption outcomes

Deeper understanding (stage 3: principles) leads to more sustained, correct, and appropriate adoption. The framework includes a feedback loop whereby actual adoption and use (learning by doing) can enhance a farmer’s understanding of principles, potentially reinforcing adoption or enabling more complex CSA practices.

The framework proposes that adoption is not determined by any single factor but emerges from the interaction between farmer cognitive development, enabling conditions (infrastructure, institutions, resources, gender equity) and technological pathways. Effective interventions must address both cognitive and structural dimensions simultaneously.

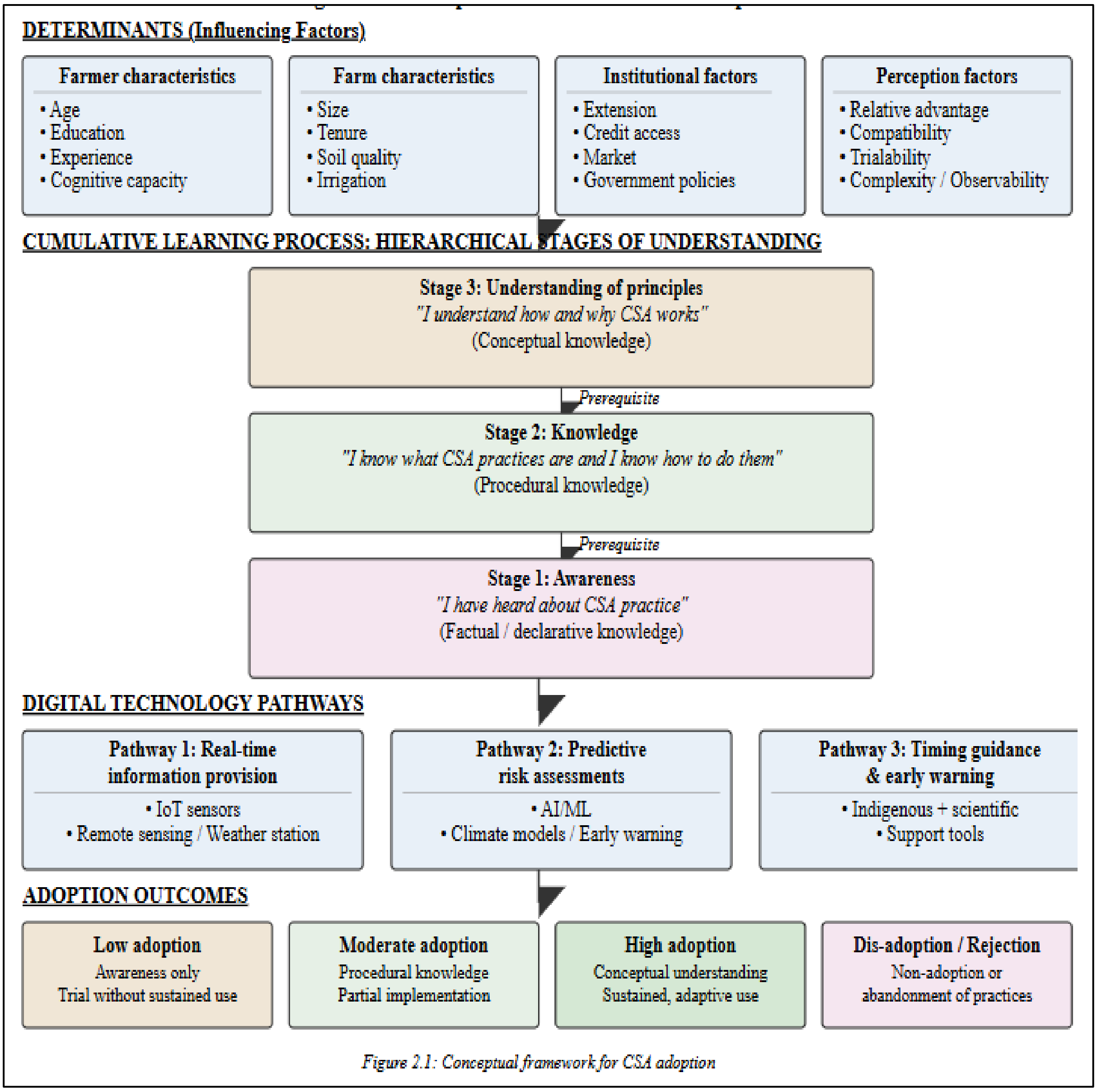

Figure 1: Conceptual framework for CSA adoption

CHAPTER III: METHODOLOGICAL FRAMEWORK

3.1 Overall research design

This thesis employs a dual-method approach: (1) a cross-sectional survey for empirical data collection in Zavala District Mozambique, and (2) a complementary systematic review following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

Empirical study: A cross-sectional study survey designed with quantitative methods, capturing data at a single point in time to provide a snapshot of CSA awareness, knowledge, understanding of principles, and adoption among smallholder farmers in Zavala District, Mozambique. This design is appropriate for describing the current state of CSA awareness and adoption and identifying factors associated with these outcomes.

Systematic review: A systematic review following PRISMA guidelines (Page et al., 2021). Synthesizing evidence from peer-reviewed literature on how digital agriculture technologies influence smallholder farmers' CSA adoption decisions across sub-Saharan Africa.

3.2 Strategies for using mixed method approach

In my dissertation, I used a mixed-method approach involving qualitative and quantitative design. My study is primarily quantitative conducted using cross-sectional survey of 400 smallholder farmers to measure awareness, knowledge, and understanding of principles and determinants of adoption. This provided statistical evidences on patterns and association. However, I incorporated qualitative elements at several stages.

First, I conducted pilot testing with 30 farmers before finalizing the questionnaires. This was a qualitative process where I observed how farmers interpreted questions and identified ambiguous terms. For example, farmers knew how to implement improved varieties but do not recognize formal terms – what I call "improved varieties paradox." This qualitative insight led to the use of composite measure to address the terminology mismatch. Thus, qualitative approach led to quantitative solutions. For instance, the composite measure revealed true familiarity of 82.5% compared to 47%. This is a terminology mismatch, not lack of exposure.

Second, during survey, enumerators documented local terminologies. This helped in explaining why knowledge sometimes exceeded awareness, which is a language issue, not knowledge gap

Third, my systematic review synthesised both qualitative and quantitative evidence from 82 studies across15 sub-Sahara African countries this captured contextual factors such as infrastructural barriers, gender constraints, institutional weakness that quantitative survey alone could not fully capture.

Fourth, I used triangulation by comparing my quantitative findings with evidence from the literature to see if they converge. The gender paradox that women have higher knowledge but lower adoption is explained by qualitative studies documenting structural barriers. The principles gap is explained by literature showing that conceptual understanding require different learning methods like farmer field schools, training, and field experimentation.

My mixed-method strategy is pragmatic. I used qualitative methods to improve measurements and interpretation and quantitative method to provide generalized evidence on patterns and associations among determinants. This method is appropriate for my research question, which asks both “what” and “why”

3.3 Study site

Empirical study context: The study was conducted in Zavala district, Inhambane province, located in southern Mozambique along the Indian Ocean coastline. Zavala lies between latitudes 24°30΄ and 25°00΄S and longitude 34°45΄ and 35°15΄E, covering an area of approximately 3500 square kilometers. The district has a tropical coastal climate with distinct wet (November to March) and dry (April to October) seasons, receiving average annual rainfall between 800 and 1200 millimeters. The average temperatures ranging from 20°C during cooler months to over 30°C in warmer months. Agriculture is the primary economic activity, with approximately 85% of the population engaged in farming. The farming system is predominantly rain-fed smallholder agriculture, with an estimated 30,000 farmers averaging 2.5 hectares per household. Major crops include cassava, maize, groundnuts, and fruit varieties such as mangoes, oranges and coconuts. The district has been the focus of numerous CSA inventions by governmental and non-governmental organizations including the ministry of agriculture, FAO, CGIAR and CARE international making it a suitable context for assessing farmers’ awareness, knowledge, and adoption of CSA practices.

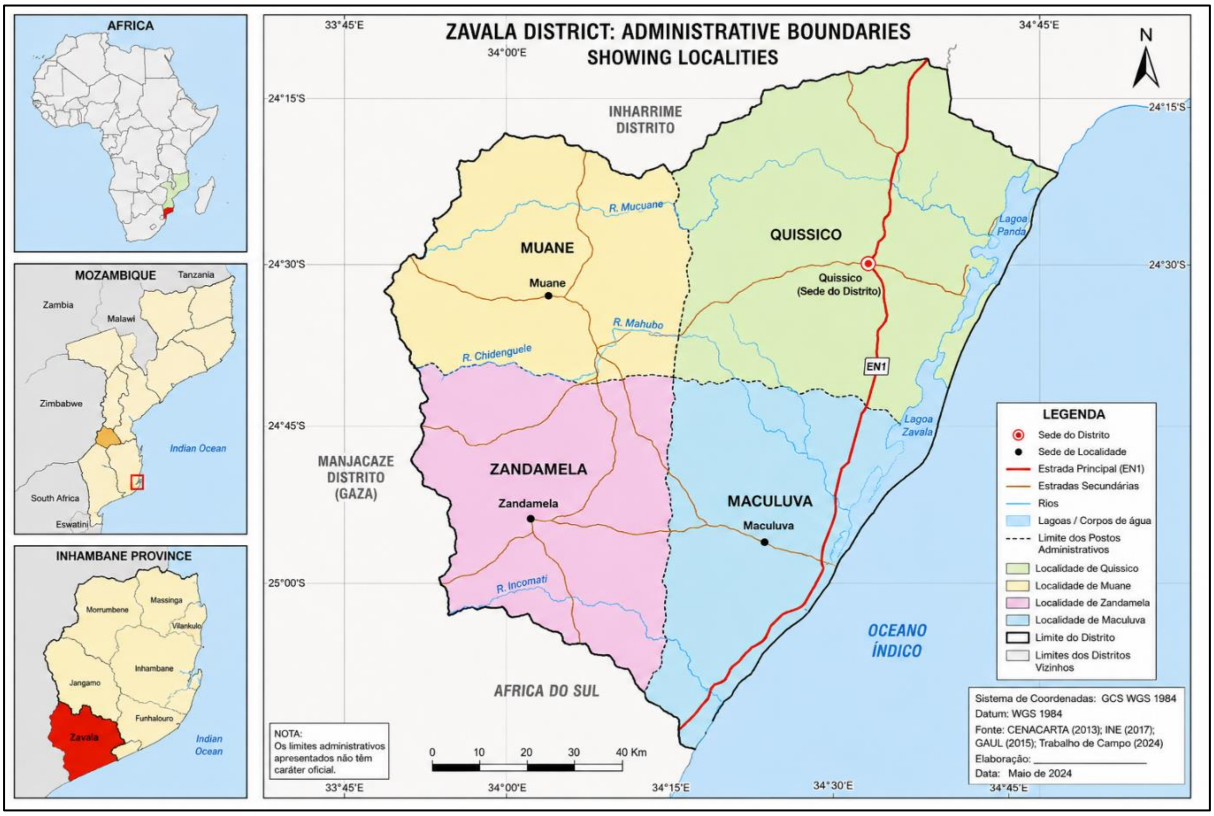

Figure 2: Map of the study area

Systematic review context: The systematic review covers sub-Saharan Africa as a whole, including studies from East Africa (Kenya, Uganda, Tanzania, Rwanda, and Ethiopia), Southern Africa (South Africa, Mozambique, Zambia, Zimbabwe and Malawi), West Africa (Ghana, Nigeria, Senegal, Mali, and Burkina Faso), and multi-country analyses. The review focuses on smallholder farmers cultivating less than two hectares, who are the most vulnerable to climate risks yet constitute the backbone of food security

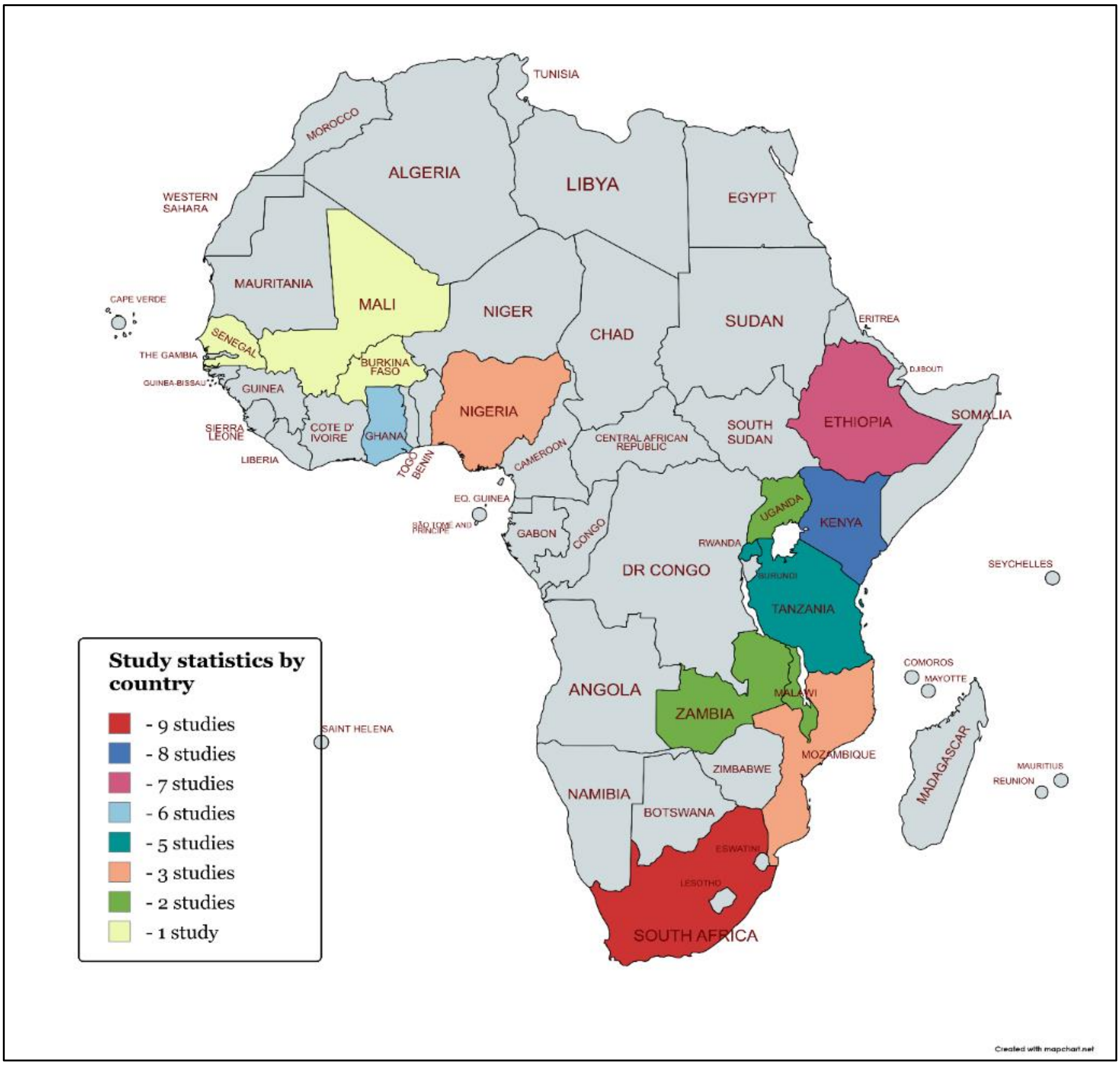

Figure 3: Map of study statistics by country

Source: MapChart. Africa: Create a custom map. Available online: https://www.mapchart.net/africa.html (accessed on 28 March 2026)

3.4 Sampling determination

The target population of this study comprised smallholder farers in Zavala District who have been engaged in agricultural production for at least three years. Smallholder farmers defined in this study as those cultivating less than two hectares of land, which is the typical farm size in the district and potentially exposed to climate vulnerabilities. The sampling frame was developed from the village register maintained by the agricultural extension offices. These registers list approximately 30,000 farmers across the district, providing a comprehensive sampling frame. The register include information on household heads, farm size, and location, enabling stratified sampling. The study used Cochran (1977) sample size determination formula for cross-sectional studies estimating a proportion

$$\mathbf{n_0 = \frac{Z^2 p(1-p)}{e^2}}$$

Where Z = 1.96 (for 95% confidence level),

P = 0.5 (maximum variability, as non-prior estimate of CSA awareness in Zavala available),

E = 0.05 (desired margin of error)

Finite population adjustment

$$\mathbf{n = \frac{n_0}{1 + \frac{n_0 - 1}{N}}}$$

Assuming a 95% confidence level (Z = 1.96), 5 % margin of error (e = 0.05) and proportion p = 0.5, the initial sample size was 384. Applying the finite population correction for N = 30,000 resulted in a final sample size of 379 respondents, which was rounded up to 400 to account for potential non-responses, incomplete questionnaires, and data entry errors, and it also served to improve the reliability of the result. Increasing sample size beyond the minimum recommended threshold is consistent with best practices in social science research because it enhances statistical power and improves the representativeness of findings. The 400 smallholder farmers selected represented a sample size sufficient for subgroup analyses (e.g. gender, education) and for detecting medium-sized effects (Cohen's $d \geq 0.3$) with power > 0.80 at $\alpha = 0.05$.

3.4.1 Sampling procedures

A multistage sampling technique was used to obtain the required number of respondents. Multistage sampling was appropriate because the study population is geographically dispersed across several administrative posts, localities, villages, and households. The use of multiple sampling stages helped to ensure adequate representation of different socio-economic and agro-ecological conditions within the district while reducing the logistical costs of data collection.

Stage 1: Zavala district was selected due to its high dependence on smallholder agriculture and its vulnerability to climate variability; besides, the district has had CSA interventions promoted in the area. It also has experienced climate-related challenges affecting agricultural productivity, making it a suitable case study for investigating climate-smart agricultural adoption decisions. Caution in generalizing absolute awareness levels to less intervention-dense areas is noted in the limitations

Stage 2: Both administrative posts in the district, namely Quissico and Zandamela, were included in the study to ensure broad geographical coverage. Including the district's two administrative pots minimized sampling bias and allowed the study to capture potential variations in farming practices and climate adaptation strategies across the district.

Stage 3: All four localities in the district were included. The inclusion of Quissico, Muane, Zandamela, and Maculuva localities ensured representation of diverse farming environments and household characteristics. These localities served as the primary sampling units for the selection of villages.

Stage 4: Villages were selected from each locality using simple random sampling. The number of villages selected from each locality was determined proportionally based on the estimated distribution of villages across the district. Out of approximately sixty-four (64) villages in the district, 32 villages were selected for the study, representing about 50 per cent of the total villages. Proportionate sampling ensured that localities with more villages contribute more respondents to the final sample, thereby improving representativeness.

Stage 5: The study conducted a systematic random sampling of households within each village. Households were listed in alphabetical order, and a sampling interval k was calculated as

$$k = \frac{N\text{village}}{n\text{village}}$$

Where Nvillage = total farming households in the village, and $n$village was allocated proportionally to the village's share of district farming population (probability proportional to size). A random start between 1 and k was selected, and every *k-th* household was chosen. If a selected household was not available after three visits, the next household on the list was substituted practicing. Smallholder farmers were selected from each sampled village. On average, 12 to 14 smallholder farmers were interviewed per village, resulting in 400 respondents across the 32 villages. The distribution ensured balanced representation of farmers across administrative posts and localities.

Overall, the sampling procedure ensured that the study achieved adequate statistical representation of smallholder farmers in Zavala District. The use of a sufficiently large sample size (n = 400) improves the precision of estimates and allows generalization of findings to the wider population of smallholder farmers in the district. The multistage sampling approach also ensured that variation in farmers' knowledge, perceptions and decision-making regarding climate-smart agriculture technologies were adequately captured across different geographical locations.

3.5 Survey instruments

A structured questionnaire was developed in three steps:

1. Literature review: Questions were adapted from validated instruments used in CSA adoption studies

2. Expert review: the draft was reviewed by three agricultural extension specialists at Eduardo Mondlane University and two district extension officers

3. Pilot testing: the questionnaire was pilot-tested on 30 farmers, (not included in the main sample) in a non-selected village. Based on pilot feedback, ambiguous terms were clarified, and the average interview time was adjusted to 30-45 minutes. No major changes to the core CSA practice list were added.

3.6 Variable measurements

Dependent variables (three levels for every 13 practices)

- **Awareness (B variables):** for each practice, farmers were asked: "have you heard of [practice]?" (0 = No, 1 = Yes). No further explanation was provided at this stage.
- **Knowledge (C variables):** only farmers who answered "Yes" to awareness were asked: "Do you know how to implement [practice] on your own farm?" (0 = No, 1 = Yes). Farmers who were not aware were coded as "0" for knowledge
- **Understanding of principles (D variables):** only farmers who answered "Yes" to knowledge were asked: "Do you understand the scientific principles behind why [practice] works?" The enumerator provided a simple explanation "for example, understanding why mulching keeps soil moist, not just how to spread mulch" (0 = No, 1 = Yes).

From these, the following composite scores were constructed:

- **Total awareness score:** sum of B variables across 13 practices (range 0-13)
- **Total knowledge score:** sum of C variables across 13 practices (range 0-13)
- **Total principles score:** sum of D variables across 13 practices (range 0-13),

For each of the thirteen practices, separate binary indicators were creates for awareness, knowledge and understanding principles yielding

- **Progression score (per practice):** 0 = no awareness; 1 = aware only (B=1, C=0, D=0); 2 = aware and knowledgeable (B=1, C=1, D=0); 3 = aware, knowledgeable and understands principles (B=1, C=1, D=1).

A total progression score was then calculated as the sum across all practices, with a maximum possible score of 39

- **Total progression score** = sum of progression scores across 13 practices (range 0-39).

- **Composite "true familiarity":** For each practice, TRUE = 1 if Awareness = 1 OR Knowledge = 1 was constructed (i.e., farmer has either heard of a practice or knows how to implement a practice). This addresses terminology mismatch.

Independent variables (socio-demographic and institutional)

- **Gender:** 1 – male, 2 – female (recorded by observation or self-report)
- **Education level:** categorical = 0 = no formal education, 1 = primary school(complete o incomplete), 2 = secondary school, 3 = tertiary/ university
- **Age:** continuous (years, self-reported)
- **Farming experience:** continuous (years of active farming)
- **Household size:** number of members living in the household
- **Group membership:** 0 – no, 1 = yes (member of any farmer cooperative, savings group, or CSA group)
- **Extension access:** 0 = no contact with extension agent in the past 12 months, 1 = at least one contact

3.7 Data collection

Data were collected over a period of six weeks from August to mid-September through face-to-face interviews. A team of six enumerators was trained over five days in questionnaire administration, ethical protocols, and data collection procedures (Creswell, 2014). Interviews were conducted in the preferred language of respondents and each interview lasted approximately thirty to forty-five minutes. Quality control measures included daily debriefing sessions, random spot checks by supervisors, and daily review of completed questionnaires for completeness and consistency.

3.8 Population and sample size determination

Empirical population and samples: The target population of this study comprised smallholder farmers in Zavala District who have been engaged in agricultural production for at least three years. Smallholder farmers are defined in this study as those cultivating less than two hectares of land, which is the typical farm size in the district. The sampling frame was developed from the village register maintained by the agricultural extension offices. These registers list approximately 30,000 farmers across the district, providing a comprehensive sampling frame. The register includes information on household heads, farm size, and location, enabling stratified sampling. The sample size of 400 was determined using Cochran & Wiley (1977) for categorical data. Finite sample size adjustment

Sample estimation for a known population

$$\mathbf{n_0} = \frac{\mathbf{Z^2 p(1 - p)}}{\mathbf{e^2}}$$

Finite population adjustment

$$\mathbf{n} = \frac{\mathbf{n_0}}{\mathbf{1} + \frac{\mathbf{n_0 - 1}}{\mathbf{N}}}$$

Assuming a 95% confidence level (Z = 1.96), 5 % margin of error (e = 0.05) and proportion p = 0.5, the initial sample size was 384. Applying the finite population correction for N = 30,000 resulted in a final sample size of 379 respondents, which was rounded up to 400 to account for potential non-responses, incomplete questionnaires, and data entry errors, and it also served to improve the reliability of the result. Increasing sample size beyond the minimum recommended threshold is consistent with best practices in social science research because it enhances statistical power and improves the representativeness of findings.

Systematic review search and screening: The search was conducted across Scopus, Web of Science, ScienceDirect and Google Scholar using Boolean operators combining terms related to digital technologies. The search string included (“remote sensing” OR “GIS” OR “geographic information system OR “IoT” OR “internet of things”) AND (“Climate-smart Agriculture” OR “CSA”) AND (“smallholder farmer” OR “small-scale farmer”) AND (“Decision-Making” OR “Adoption”) AND (“sub-Saharan Africa” OR “Africa”). These searches focused on peer-reviewed articles and institutional reports published between 2017 and 2025.

3.8.1 Sampling technique

Empirical context: A multistage sampling technique was employed to obtain the required number of respondents. Multistage sampling was appropriate because the study population is geographically dispersed across several administrative posts, localities, villages, and households. The use of multiple sampling stages helped to ensure adequate representation of different socio-economic and agro-ecological conditions within the district while reducing the logistical costs of data collection.

Stage 1: Zavala district was purposely selected due to its high dependence on smallholder agriculture and its vulnerability to climate variabilities, and CSA interventions promoted in the area. It also has experienced climate-related challenges affecting agricultural productivities, making it a suitable case study for investigating climate-smart agricultural adoption decisions. Besides, the sandy soil is nutrient poor and exacerbates vulnerability.

Stage 2: Both administrative posts in the district, namely Quissico and Zandamela, were included in the study to ensure broad geographical coverage. Including all administrative pots minimized sampling bias and allowed the study to capture potential variations in farming practices and climate adaptation strategies across the district.

Stage 3: All the four localities in the district were included. The inclusion of Quissico, Muane, Zandamela, and Maculuva localities ensured representation of diverse farming environments and household characteristics. These localities served as the primary sampling units for the selection of villages.

Stage 4: Villages were selected from each locality using simple random sampling. The number of villages selected from each locality was determined proportionally based on the estimated distribution of villages across the district. Out of approximately sixty-four (64) villages in the district, 32 villages were selected for the study, representing about 50 percent of the total villages. Proportionate sampling ensured that localities with more villages contribute more respondents to the final sample, thereby improving representativeness.

Stage 5: Households practicing smallholder farming were selected from each sampled village. List of farming households were obtained with the assistance of village leaders and local authorities. Where complete household list were available, simple random sampling was used to select respondents. In situations where list was incomplete, systematic sampling was applied by selecting households at regular intervals. On average, 12 to 14 smallholder farmers were interviewed per village resulting in 400 respondents across the 32 villages. The distribution ensured balanced representation of farmers across administrative posts and localities.

Overall, the sampling procedure ensured that the study achieved adequate statistical representation of smallholder farmers in Zavala District. The use of sufficiently large sample size (n = 400) improves the precision of estimates and allows generalization of findings to the wider population of smallholder farmers in the district. The multistage sampling approach also ensured that variation in farmers' knowledge, perceptions and decision-making regarding climate-smart agriculture technologies were adequately captured across different geographical locations.

Systematic review context: The initial search result yielded 9,246 records. After removing duplicates (3918), 5328 records were screened by title and abstract, excluding 4892 record, full-text review of 436 records resulted in 76 included studies. An additional 10 records from other sources were assessed, with 6 meeting eligibility criteria, bringing the total to 82 studies included for synthesis.

3.9 Data collection methods

Data were collected through face-to-face interviews using a structured questionnaire developed based on the literature and adapted to the local context following pilot testing with 30 farmers. Pilot testing assessed question clarity, cultural appropriateness, and response variability. The final instrument included sections on farmer demographics and farm characteristics, awareness, knowledge and principles understanding of thirteen CSA practices, perceptions of CSA technology attributes socio-psychological factors, institutional support, asset availability and adoption status and intensity.

Interviews were conducted in the local language (Chope) by trained enumerators with prior experience in agricultural survey data collection. Enumerators received 3 days of training covering survey protocols, question administration and ethical consideration. Data collection tool 6 weeks (2 August and 16 September 2025) with interviews lasting approximately 30-45 minutes.

Systematic review data extraction: Data extraction employed a standardized framework developed to capture study characteristics (author, year, geographical location, methodology, and key findings). Other parameters included technology focus (type of remote sensing, GIS, IoT, and AI/ML). Additionally, decision-making influence (mechanism and evidence of influence on farmers decisions); CSA practices examined (specific practices and reported adoption rates); adoption determinants (enablers and barriers characterised by factor type). The review further considered integration approaches (how technologies were deployed and with what support systems), and finally, contextual factors (socio-economic, infrastructural, and institutional conditions). The study employed Scispace AI data extraction tool to ensure accuracy, with all extracted data verified manually by authors.

3.9.1 Survey instruments

The questionnaire captured **socio-demographic characteristics** (gender, age, education level, farming experience, farm size, and income sources). **Awareness (B variables)** included 13 CSA practices in which for each practice, the farmers were asked, “Have you heard of (practice)?” (0 = No, 1 = Yes) responses. The practices included agroforestry, drought tolerant crops, improved varieties, conservation tillage, integrated pest management (IPM), rainwater harvesting, organic farming, intercropping, crop rotation, cover cropping, Biofertilizers, soil fertility management, and water-efficient irrigation. **Knowledge (C variables)** where for each practice, farmers who reported awareness were asked, “Do you know how to implement (practice)?” (0 = No, 1 = Yes). Farmers who had not heard of the practice were coded as “0” for knowledge. **Understanding of principles (D variables)** for each practice, farmers who reported knowledge were asked, “Do you understand the principles behind the practice?” (0 = No, 1 = Yes). Farmers were provided with simple explanations of what “principles” for each practice meant (e.g. understanding why the practice works, not just how to do it). Farmers’ perceptions of CSA technologies characteristics (relative advantage, compatibility, flexibility, triability, observability) coded as scale of 1-5. Institutional factors such as market access, credit access, extension contacts, and cooperative memberships all coded as (dummy: 0 = no, 1 = yes) and social capital/network coded as (dummy: 0 = no, 1 = yes).

3.9.2 Variable measurements

The study employed multiple variable types to capture complexity of farmer understanding and factors influencing it. **Three primary dependent variables** (total awareness score, total knowledge score and total principles score) were constructed such that each dependent variable was calculated as a sum of affirmative responses for all thirteen practices against its variables, yielding a potential range of 0-13. These continuous variables (range) measured the breadth of practices farmers had heard about (awareness), knew how to implement (knowledge), and understood underlying concepts (principles) consistent with composite index construction approach. For each of the thirteen practices, separate binary indicators were creates for awareness, knowledge and understanding principles yielding a progression score. In the progression score for each practice, a farmer was assigned a level score (0 = no awareness, 1 = aware only, 2 = aware and knowledge, 3 = aware, knowledge, and understand principles). A total progression score was then calculated as the sum across all practices, with a maximum possible score of 39. **Independent variables** included gender (1 = male, 2 = female), level of education (0 = no education, 1 = primary, 2 = secondary, 3 = tertiary/university), age (in yeas as continuous), farming experience (in years as continuous), household size (number of members as continuous), group membership (0 = no, 1 = yes), and extension access (0 = no contact in past 1year, 1 = at least one contact).

3.10 Data analysis techniques

Empirical study: Data were analysed using IBM SPSS Statistics (version 26). The analysis proceeded in several stages corresponding to research objectives.

Descriptive statistics were computed for all variables. For continuous variables (age, faming experience, far size, and annual income), means and standard deviations were calculated. For categorical variables (gender, education level, cooperative membership, and extension contact), frequencies and percentages were reported. The study considered tabulation of distribution of farmers by awareness level (very low, low, moderate, and high).

Comparative analysis: t-tests, Mann-Whitney U, and ANOVA

Paired t-tests (H1a)

To test whether there is statistically significant difference between awareness levels and knowledge levels across the 13 CSA practices; paired t-tests were conducted. This approach follows established practice in CSA adoption research where pre-and post- intervention or paired measurements are compared (Maseko, 2005; Mmbando, 2025). The paired design accounts for the fact that awareness and knowledge scores come from the same farmer for each practice

Independent samples t-tests and Mann-Whitney U tests (H1b)

To compare male and female farmers on total awareness, total knowledge and total understanding of principles scores, the study adopted independent samples t-tests. Levene's test for equality of variance was used and where variances were unequal, adjusted t-statistics were reported, since the principle scores showed mild skewness, Mann-Whitney U test was performed as a non-parametric alternative to confirm the t-tests results. The use of both parametric and non-parametric tests for gender comparisons is widely documented in CSA literature (Hailemariam et al., 2024; Rudrapal, 2021; Wamaitha et al., 2022).

One-way ANOVA with Tukey HSD post-hoc (H1c)

To compare means across education levels (no formal, primary, secondary, and tertiary), the study used one-way analysis of variances (ANOVA). Where ANOVA indicated significant differences ($p< 0.05$), post-hoc comparison were conducted using Tukey's Honestly Significance Difference (HSD) to identify which specific education levels differed. This approach has been applied to examine the effect of education on CSA adoption in multiple studies (Dhanalakshmi et al., 2021; Nchanji et al., 2025).

Bivariate associations: Pearson and Spearman Correlations (H1d)

The relationships between total awareness, total knowledge, and total principles scores were examined using both Pearson and Spearman correlation coefficients. Pearson's r was calculated for normally distributed continuous variables (total awareness vs, total knowledge). Spearman's rank correlation (ρ) was used for variables that were not normally distributed or for ordinal data (total principles), consistent with recommendations in the agricultural methodology literature (Kozak et al., 2012; Flanclin et al., 2024). Correlation strength was interpreted as weak ($|r| < 0.3$), moderate ($0.3 \leq |r| < 0.7$), or strong ($|r| \geq 0.7$). The correlation model is specified as

Pearson correlation

$$r = \frac{\sum_{i=1}^{n}(X_1 - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_1 - \bar{X})^2 \sum_{1=1}^{n}(Y_1 - \bar{Y})^2}}$$

Spearman correlation

$$\rho = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2 - 1)}$$

The combined use of both coefficients follow recent studies that report both Pearson and Spearman correlations to address normality assumptions (Karim & Thiel, 2026). The study used Chi-square tests of independence to asses associations between categorical variables such as education level and cooperative membership, gender and training received, and gender and adoption level. For 2 x2 tables, odd ratios (OR) with 95% confidence interval were calculated to quantify the strength of association

Factor analysis: Principle component analysis (H2a)

The Principle component factor analysis was conducted on the five items measuring Rogers' perceived attributes (relative advantage, compatibility, complexity, trialability, observability). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were used to assess the suitability of the data for factor analysis. Factors with eigenvalues greater than 1 were retained. This methodological approach has been used to validate the dimensionality of Rogers' innovation attributes in agricultural contexts (Dorji et al., 2022; Morris et al., 2025; Yuniarsih et al., 2024). The factor analysis enabled testing of H2a: whether the five attributes ae empirically distinguishable or collapse into a single dimension.

Composite measures

To address terminology mismatch (the “improved varieties paradox”) a composite measure was constructed. For each practice, a binary variable “true familiarity” was defined as awareness = 1 OR knowledge = 1. This composite measure was compared with simple awareness percentages to identify practices where knowledge exceeds awareness, indicating that farmers possess practical understanding without recognizing formal terminology. This approach is consistent with recommendations from DNA fingerprinting studies that demonstrate high misclassification rates in farmer self-reports of improved varieties (Kosmowski et al., 2018; Wineman et al., 2020)

Regression analyses

Multiple linear regression (H2a, H3b, H3c, H3d)

Multiple linear regression (enter method) was used to identify factors associated with total awareness, total knowledge, and total understanding of principles scores separately. For each dependent variable, the same set of independent variables was entered: age, gender, education level, farming experience, and annual income. The linear regression model is specifies as

$$\boldsymbol{Y_i = \beta_0 + \beta_1 X_{\{1i\}} + \beta_2 X_{\{2i\}} + \cdots + \beta_k X_{\{ki\}} + \varepsilon_i}$$

- Y = total awareness score (0-13), total knowledge score (0-13), or total principles score (0-13)
- β_0 = intercept

  $\beta_1 \ldots \beta_5$ = regression coefficients
- ε = error term
- $\boldsymbol{Y = \beta_0 + \beta_1(\text{Age}) + \beta_2(\text{Gender}) + \beta_3(\text{Education}) + \beta_4(\text{Farming Experience}) + \beta_5}$ $\boldsymbol{(\text{Annual Income}) + \varepsilon}$

Standard coefficients (beta) were reported to compare the relative importance of predictors. Model fit was assessed using R^2 and adjusted R^2, and overall model significance was tested with an F-test. Variance inflation factor (VIF) were examined to check for multicolinearity (no VIF exceeded 2.0). The use of multiple linear regression to explain variance in awareness, knowledge, and adoption outcomes is well established in CSA research (Dhanalakshmi et al., 2021; Nurdin et al., 2020). The r2 from these models was used to test H3d, which posits that the combination of demographic, institutional, and perceptual factors explains significant variance in adoption outcomes

R-Squared $\boldsymbol{R^2 = 1 - \frac{\sum(Y_i - Y_i)^2}{\sum(Y_i - Y)^2}}$, **Adjusted R-Square**$\boldsymbol{R^2_{\{adj\}} = 1 - \left(\frac{n-1}{n-k-1}\right)(1 - R^2)}$

Multinomial logistic regression (H2b, H3a, H3b, H3c)

Multinomial logistic regression was employed to identify factors differentiating; low, moderate, and high adoption levels. The dependent variable was adoption level (low = reference category). Independent variables included age (continuous), farming experience (continuous), gender (dummy: 1 = male. 0 = female), extension contact (dummy: 0 = no contact, 1 – at least one contact), and cooperative membership (dummy: 0 = not a member, 1 = member). The model was estimated using maximum likelihood. Result were reported as odds ratios (OR) with associated standard errors and p-values. Model fit was assessed using the likelihood ratio chi-square test. The multinomial logit model is specified as

$$\boldsymbol{ln\left(\frac{P(Y_i = j)}{P(Y_i = 0)}\right) = \beta_{\{0j\}} + \beta_{\{1j\}X_{\{1i\}}} + \beta_{\{2j\}X_{\{2i\}}} + \cdots + \beta_{\{kj\}X_{\{ki\}}}}$$

Where Y_i= 0 represents high adoption, j = 1 represents moderate adoption, and j = 2 represents high adoption. The probability of each adoption level is given by:

$$\boldsymbol{P(Y_i = j) = \frac{e^{X_i\beta_j}}{1 + \sum_{k=1e^{X_i\beta_k}}^{J}}, \qquad P(Y_i = 0) = \frac{1}{1 + \sum_{k=1e^{X_i\beta_k}}^{J}}}$$

The odds ratio for each predictor is computed as $\boldsymbol{OR = e^{\beta}}$

Multiple linear regression is the standard model when the dependent variable has more than two unordered categories (low, moderate, high adoption) (Makamane et al., 2023; Mujeyi et al., 2020). This approach has been widely applied in CSA adoption research to identify determinants of adoption levels. The model enables testing of H2b (compatibility and trialability as strongest predictors), H3a (extension contact frequency is positively associated with adoption), and H3c (age negatively associated, experience positively associated).

Model fit summary for objective 3 (H3d)

For the linear regression models (total awareness, total knowledge, and total principles), the R^2 and adjusted R^2 values were reported together with F-statistics and p-values. For the multinomial logistic regression model, the likelihood ratio chi-square test (χ^2) and degree of freedom were reported. All statistical tests were two tailed and before running parametric tests (t-tests, ANOVA, Pearson correlation, linear regression), assumptions were checked and in cases where assumptions were violated, non-parametric alternatives (Mann-Whitney U, Spearman correlation) were used or robust standard errors were employed (for regression). The comprehensive reporting of model fit follows standard practice in adoption studies (Asante et al., 2024). Results were considered statistically significant when $p < 0.05$, with additional reporting of $p < 0.01$ and $p < 0.001$ where applicable.

This analytical strategy is consistent with methodological best practices in agricultural social science research (Ahn et al., 2026; Kozak et al., 2012).

Systematic review technique: Thematic synthesis organized data into key domains identified in the research questions. Given the heterogeneity in study designs, technology types, and outcome measures, narrative synthesis was conducted following Petticrew & Roberts (2008) guidance for narrative synthesis in systematic reviews. Thematic analysis identified patterns and relationships across studies. The study used quality assessment method adapted from the Risk-Of-Bias Visualization (ROBVIS) checklists Mcguinness (2020), with studies rated as low risk ($n = 69$), some concerns ($n = 11$), or high risk ($n = 1$). High-risk study retained but given less weight in the synthesis.

The null and alternative hypotheses used in this study are as stated in section 1.5.

3.10.1 Assumption testing and corrective measures

Prior to inferential analyses, statistical assumptions underlying each analytical technique were assessed. For independent sample t-tests, the assumption of homogeneity of variance was violated, as evidences by significant Levene's test results. This prompted the use of Welch's t-test to adjust the degree of freedom and provide more reliable significance estimate under unequal variance conditions. Furthermore, mild skewness in the distribution of principles scores suggested potential departure from normality; therefore, Spearman's (p) was conducted as a non-parametric alternative to validate robustness of the findings.

For one-way ANOVA models examining educational differences, violations of homogeneity of variance assumption were detected for some of the dependent variables. To address this issue, Welch's ANOVA was used as a robust alternative to conventional ANOVA. In addition, Kruskal-Wallis tests were conducted as non-parametric counterparts to confirm the consistency of the observed group differences. The eta-squared and omega-squared were reported as the effect size.

In factorial analysis stage, the suitability of the data for dimensional reduction was evaluated using Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Tests of

Sphericity. These test confirmed that correlation matrix contained sufficient common variance for factor extraction, indicating that the assumptions required for principal component analysis were met.

For multilinear regression models, diagnostic procedures were performed to evaluate normality of residuals, homoscedasticity, independence of errors, and multicollinearity. These assumptions were assessed using Shapiro-Wilk tests, Q-Q plots, Durbin-Watson statistics, and Variance Inflation Factors (VIF), respectively. No serious violation was reported; therefore, standard multiple linear regression procedures were retained.

For ordered logistic regression, the proportional odds assumptions was tested using the Brant tests. The non-significant Brant test results indicated that the proportional odds assumption was satisfied, supporting the appropriateness of the ordered logistic specification. Finally, because total progression scores were naturally bounded between 0-39, Tobit regression was employed as a robustness check to account for censoring effects and potential floor and ceiling constraints that could bias ordinary least square estimates.

3.11 Ethical considerations

Empirical study ethics: The study was conducted in accordance with the ethical principles for research involving human subjects. Ethical exemption letter was obtained from the Eduardo Mondlane University Review Board. Permission to conduct the research in Zavala district was secured from District directorate of Agriculture and local administrative authorities (Secretários de Bairos). Accompanied by GUIA DE MARCHA (marching guide) accented to by the district agricultural officer of Zavala district services for economic activities (SDAE), verbal consent was obtained from the respondents (stallholder farmers) with freedom of withdrawal or non-participant in the data collection at any point of the survey granted to respondents.

Informed consent: prior to any data collection, the purpose, procedures, risks, and benefits of the study were explained to each potential participant in the local language by trained local enumerators. Farmers were informed that participation was entirely voluntary, and they could withdraw at any time without penalty or loss of access to extension services, and that their decision to participate or not would not affect any services they received from government or non-governmental organizations. Oral consent was obtained and respondents who were uncomfortable taking part in the interview were thanked and not interviewed further.

Confidentiality and anonymity: no personal identifier (names, identity, numbers, or exact homestead locations) were recorded on the questionnaire. Each respondent was assigned a unique study identification code. All data entered into a password-protected computer, and stored on an encrypted drive accessible only by lead researcher.

Compensation and non-maleficence: the study posed no physical or psychological risks to participants. Enumerators were trained to avoid causing distress and stop interview immediately if a participant showed signs of discomfort. No sensitive personal information collected for study.

Cultural sensitivity: interviews were conducted by enumerators matched by gender (female enumerators interviewed female farmers and male enumerators interviewed male farmers) to respect local customs and facilitate open communication. Interviews took place at a time and location chosen by participant (home, field or community meeting place). Questions were framed in a non-judgmental manner, and enumerators were instructed to avoid any language that could be interpreted as criticism of traditional farming practices.

Community-level consent: before starting household interviews, the research team met with village administrative heads and local extension agents to explain the study objectives and procedures. Verbal community consent was obtained, and community members were invited to ask questions on what needed clarification and responses from the interview team. This step ensured that research was conducted transparently and with local endorsement.

Systematic review ethics: As a secondary research synthesis, the systematic review did not require ethical approval. However, the review followed PRISMA guidelines to ensure transparency and reproducibility. All included studies were peer-reviewed or from credible sources (foundational studies) and findings are reported without selective omission.

3.12 Study limitations

Despite careful planning, several challenges arose during the fieldwork that required adaptive responses.

Access to remote households: Zavala district has dispersed settlements, with some villages located more than 10km from the nearest all-weather road. Some feeder roads remain degraded with several homesteads accessible by foot or motorcycles. The ream had to higher local guides and extend the data collection period by 2 weeks to reach all sample households.

Participant availability and fatigue: many farmers work in their fields from early morning until afternoon. Interviews conducted during peak farming hours often resulted in refusals or request to rescheduling. The team adapted by conducting interviews in the late afternoon or early evening, but this required carrying headlamps and working long hours. Some farmers were visibly tired after full day physical labor, which may have affected the quality of responses to open-ended questions on principles.

Gender dynamic and reluctance to speak. In some male-headed households, male household heads initial insisted on answering for the entire household, including questions about women's awareness and knowledge. Female enumerators were essential in gently negotiating separate interviews with women, sometimes away from the homestead.

Low literacy levels. Many farmers could not read the response cards or consent forms. Enumerators had to read every question and response option aloud, which slowed the pace of interviews and increased the risk of fatigue. Visual aids (picture practices) were used, but not all practices could be easily illustrated.

Language and terminology barriers: although the questionnaire was translated into Portuguese some CSA terms like "improved varieties," had no direct equivalent. Farmers often used different local names or described practices without recognizing the formal term. This required enumerators to use short descriptions and examples alongside the written question, which increased interview duration and introduced minor variability in how questions were interpreted. The composite measure (awareness OR knowledge) was developed partly in response to this challenge.

Seasonal constraints on recall: the survey was conducted at the end of the dry season (August-September), several months after the previous harvest. Some farmers had difficulty recalling which practices they had used in the previous season, particularly for practices like cover cropping that are implemented as specific times, to aid recall, enumerators used a seasonal calendar, but some recall biased likely remains.

Mitigation measures summarized: despite these challenges, the team achieved high response rate (99.5%, with only 2 refusal out of 402 households approached). The use of local enumerators, extended training, pilot testing, gender matching, and flexible scheduling all contributed to successful completion of data collection. The limitation introduces by these challenges are acknowledge in section 3.7.

Systematic review limitations: (i) uneven geographic coverage, with Eastern and Southern Africa overrepresented relative to Western and Central regions. Central Africa's absence from a single-country study limits generalizability across the region. (ii) Peer-reviewed literature may overrepresented successful pilots and underrepresent failures, introducing publication bias. (iii) Most included studies are cross-sectional, limiting understanding of sustained technology influence over multiple seasons. (iv) Heterogeneity of technology types, outcome measures, and methodological approaches limit comparability across studies and precludes meta-analysis. (v) The rapid evolution of digital technologies means findings may require updating as technologies and adoption patterns evolve.

CHAPTER IV: PUBLICATION MANUSCRIPT I

Title: Farmer Awareness, Knowledge and Understanding: A Multi-Level Assessment of Adoption of Climate-Smart Agricultural Practices among Smallholder Farmers.

Accepted for publication in Frontiers in Climate - Climate Adaptation

Published on 16/06/2026

Authors Contributions:

Calvince Andele Ogutu: Writing original draft, investigation, visualization, conceptualization, methodology development, data curation, formal analysis

Eunice Cavane: Writing – review & editing, conceptualization, methodology development, data analysis, validation, supervision

Title: Farmer Awareness, Knowledge and Understanding: A Multi-Level Assessment of Adoption of Climate-Smart Agricultural Practices among Smallholder Farmers.

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ABSTRACT

Climate-Smart Agriculture (CSA) offers potential solutions for enhancing agricultural productivity, building resilience, and mitigating climate change. However, successful implementation depends on farmer's understanding of CSA practices across multiple levels-from basic awareness to deep conceptual knowledge. This study assessed smallholder farmer's levels of awareness, knowledge and understanding of principles of 13 CSA practices, and examines variations by gender and education. A cross-sectional survey was conducted with 400 smallholder farmers and data collected on three levels for each practice - awareness (heard of practice), knowledge (know how to implement), and understanding of principles (comprehend underlying concepts). Descriptive statistics, t-test, ANOVA, chi-square tests, correlation analyses, and progression analysis performed. Non-parametric alternatives (Mann-Whitney U, Kruskal-Wallis, Spearman correlation) confirmed parametric results. Awareness ranged from 47% (improved varieties) to 100% (intercropping). Knowledge levels were generally lower with least gap for rainwater harvesting (81.0% aware vs 39% knowledge). Three distinct patterns emerged: (1) awareness exceeding knowledge (superficial awareness) for rainwater harvesting, agroforestry, and bio-fertilizers; (2) knowledge exceeding awareness (terminology mismatch) for improved varieties and soil fertility management; and (3) aligned awareness and knowledge for remaining practices. Women had significantly higher awareness (11.34 vs7.47 practices, $p < 0.001$), knowledge (10.21 vs 6.82, $p < 0.001$), and understanding of principles

(9.45 vs6.24, $p < 0.001$) than men. Education had a powerful effect (F=749.78, $p < 0.001$), with secondary education representing critical threshold. Chi-square tests revealed that less-educated farmers had 0% awareness of four practices (conservation tillage, cover cropping, soil fertility management, water efficient irrigation), indicating complex exclusion from extension messaging. Composite measures addressing terminology mismatches showed true familiarity with improved varieties at 82.5% compared to 47.0% awareness. The farmer population was polarized – 54.2% had high awareness (10-13 practices) whereas 15.0% had very low awareness (0-3 practices). We conclude that effective CSA promotion requires targeted awareness campaigns for low-awareness technologies, gender responsive approaches that recognize women's high awareness, and education sensitive extension that builds on the strong education gradient.

Keywords: Climate-Smart Agriculture, awareness, knowledge, Principles, smallholder farmers.

1 INTRODUCTION

1.1 Background

Climate change poses unprecedented challenge to global agriculture systems, threatening food security and livelihoods, particularly among smallholder farmers in developing countries (Lipper et al., 2014; Tilman et al., 2011). The increasing frequency of drought, erratic rainfall patterns, and extreme weather events has intensified the vulnerability of agricultural systems, especially in sub-Saharan Africa where rain-fed agriculture predominates (Harvey et al., 2014). In response to these challenges, climate-smart agriculture (CSA) has emerged as an integral approach to addressing the triple goals of sustainably increasing agricultural productivity, enhancing resilience to climate shocks, and reducing greenhouse gas emissions where possible (FAO, 2013).

The CSA framework encompasses a diverse range of practices, including agroforestry, conservation tillage, improved crop varieties, integrated pest management, rainwater harvesting, and soil fertility management (Chandra et al., 2017). These practices are designed to work synergistically, building the adaptive capacity of farming systems and the mitigation potential of agriculture (Campbell et al., 2014). Despite the recognized potential of CSA, adoption rates remain suboptimal in many smallholder-farming contexts across Africa (Branca et al., 2021; Zougmoré et al., 2016). A systematic review by Finizola e Silva et al. (2024)

identified over forty factors influencing CSA adoption, categorised as personal, farm-related, financial, environmental and informational factors.

1.2 The challenge of technology adoption

Research has consistently demonstrated that adoption of agricultural technologies is a complex process influenced by multiple interacting factors (Feder et al., 1985; Rogers, 2003). Among the most cited barriers to adoption are limited access to information, credit, inputs, and markets (Ogada et al., 2021). However, a growing body of literature emphasizes that farmers' lack of awareness and knowledge about CSA practices is a primary constant (Teklewold et al., 2013; Kassie et al., 2015). The systematic review by Mulungu et al. (2025) reveals that 76% of studies reported increased adoption of good agricultural practices following information interventions, while 60% demonstrated improved awareness highlighting the critical role of information availability and access in technology uptake.

The relationship between information and adoption is not straightforward, however, recent research by Miehe (2025) challenged the prevailing wisdom that "information leads to adoption," demonstrating that correcting inflated expectations about improved seed performance actually reduced short-term adoption but led to more realistic decision-making. This finding underscores the importance of understanding farmers' mental models and expectations when designing extension interventions.

1.3 Conceptual Framework: levels of understanding

Understanding farmers' cognition regarding agricultural innovations is complex and multi-dimensional. Drawing on educational psychology Krathwohl (2002) and diffusion of innovation theory Rogers (1983, 2003), we conceptualize farmers' understanding as operating at three distinct levels: **(1) awareness level** – in this dimension, a farmer has heard of the CSA practice and knows of its existence, this represents declarative knowledge at its most basic level (Leslie, 2016). Awareness is necessary but not sufficient for adoption. Ogunyiola et al. (2022) emphasize that awareness alone does not guarantee adoption as farmers' local knowledge systems may interact with introduced practice in complex ways. **(2) Knowledge level** where a farmer understands how to implement the practice. This is procedural knowledge, which is the ability to perform the practice (Ryle, 1994). Farmers at this level can potentially apply the practice on their farms, though they may face resource, structural or institutional hurdles. **(3) Understanding of principles** – the level at which a farmer comprehends the underlying scientific principles and concepts. This represents conceptual knowledge – understanding why the practice works (Krathwohl, 2002). Farmers at this level can adapt practices to their specific context and troubleshoot problems independently, which is critical for sustained adoption and innovation (Glendenning, 2010). These three–level framework aligns with Bloom's revised taxonomy Leslie (2016) and provides a more nuanced assessment of farmer cognition than simple binary measures of awareness or adoption commonly used in agricultural research (Udry et al., 2024; Evenson & Gollin, 2003).

Conceptual Framework

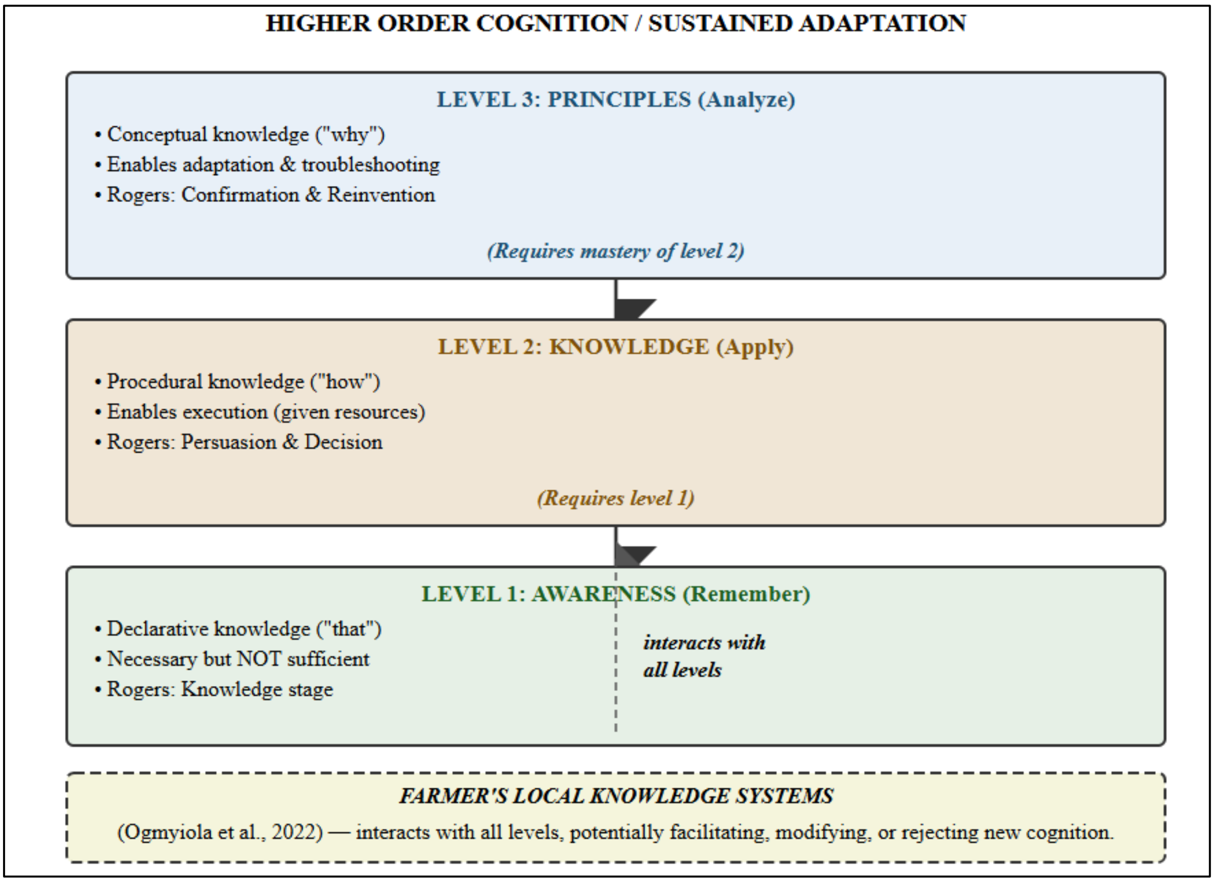

Figure 4: Conceptual framework for CSA knowledge system

1.4 Previous research on awareness knowledge

Previous studies have documented varying evidence on farmer awareness of agricultural technologies. Marenya & Barrett (2007) found that intercropping and crop rotation were deeply embedded in smallholder farming systems in western Kenya, suggesting indigenous knowledge transmitted across generations. Partey et al. (2018) reported that 95% of farmers in Ghana were aware of CSA concepts, with agroforestry and water management practices among the most widely recognized. The role of information and communication technologies (ICTs) has received increased attention. The systematic review by Mulungu et al. (2025) documented that ICT interventions including mobile apps, SMS, educational videos and voice-calling services have demonstrated positive impacts on awareness, adoption, yield and income.

However, the success of these interventions depends on well designed messaging, adequate user training, and integration with complementary interventions.

The study by Okori et al. (2022), Makapela et al. (2025), and Kangogo et al. (2024) show that farmer-to-farmer learning and community-based training approaches significantly improve agricultural productivity and technology adoption. For instance, farmer-led extension and training initiatives have increased crop yields by 30-40% and improved farm income among smallholder farmers in sub-Saharan Africa. Evidence on agricultural knowledge and gender differences show mixed results. A recent study in Tanzania by Manono et al. (2025) noted male domination in climate-adoption decisions at the household levels due to ownership and control of land and access to agricultural support services. However, Nchanji et al. (2025) in Eastern Uganda and Bogweh et al. (2025) in Tanzania reported that women had higher access to and sustained use of improved common bean varieties, indicating that gender dynamics are context specific and may be shifting with target interventions. Gulati & Magnan (2026) using data from India, found that women's agricultural networks are approximately 26% larger than men's, but these networks rarely overlap, meaning extension targeting only men reaches only part of the household's learning space. A systematic review by Finizola e Silva et al. (2024) Awoke et al. (2024), and Boudalia et al. (2024) highlighted gender as one of several personal factors influencing CSA adoption, though its effects are often mediated by other variables. Mutenje et al. (2019) provide additional evidence on gender perspectives in CSA adoption.

Across multiple studies, education has stood out as a strong predictor of agricultural knowledge and adoption. Goni et al. (2025) found that level of education was significant ($p < 0.05$) in influencing adoption of CSA practices in Ethiopia, Ghana and Nigeria. Asfaw & Admassie (2004) identified education as critical human capital influencing adoption, reporting that educated farmers make better decisions because they can read extension materials and understand technical information. A meta-analysis by Adewopo et al. (2025), Kendall et al. (2022), Coggins et al. (2022) confirmed that education is one of the socioeconomic determinants of technology adoption across multiple contexts, with higher educational attainment increasing the likelihood of using digital agricultural technologies. Similarly, Finizola e Silva et al. (2024) found out that level of education was a key personal factor significant in influencing adoption of CSA practices.

1.5 The importance of local knowledge and terminologies

Recent scholars have emphasized the importance of integrating farmers' local knowledge with scientific evidence for successful CSA upscaling. For instance, Ogunyiola et al. (2022) argue the need for policymakers and academics to rethink how local knowledge held by smallholder farmers hold potential for CSA adoption. Their review noted that only eight of thirty articles addressed challenges regarding inclusion or exclusion of local knowledge in CSA practices, thereby presenting a significant research gap.

Terminology plays a crucial role in how farmers perceive and adopt new technologies. Rurii & Nzengya (2026) emphasizes that adoption is not one-size-fits-all and that farmers must select practices based on their individual capacity to implement them, ensuring chosen practices are both contextually appropriate and feasible for each farmers' unique resource and constraints. This insight is directly relevant to understanding the improved variety paradox documented in several studies (Miehe, 2025; Nchanji et al., 2025).

Kosmowski et al., (2018) highlight that varietal adoption based on household survey has mostly relied on farmers' responses to varietal identification, but this method can give biased estimates, if farmers' responses are unable to identify improved varieties as a group or by name. Their research using DNA fingerprinting in Ghana and Zambia found large variations in adoption estimates compared to farmers self-reports, emphasizing the need for careful terminology and measurement approaches.

1.6 Research gaps and rationale

Despite the existing research on climate-smart awareness and adoption, several gaps remain. Firstly, most studies treat awareness and knowledge as unidimensional, failing to distinguish between superficial awareness, procedural knowledge and deep conceptual understanding (Krathwohl, 2002; Leslie, 2016). Secondly, few studies systematically compare these three levels across a comprehensive set of CSA practices (Teklewold et al., 2013; Kassie et al., 2015). Thirdly, the relationship between awareness and knowledge – whether they are aligned or mismatched – has received limited attention (Marenya & Barrett, 2007). Fourthly, the phenomenon where knowledge exceeds awareness (suggesting terminology mismatch) is under-explored as highlighted by (Kosmowski et al., 2018; Fisher & Carr, 2015). Fifth, the role of understanding of principles as a distinct level of cognition has not been adequately addressed in the agricultural literature (Glendenning, 2010; Marenya & Barrett, 2007).

1.7 Significance of the study

By identifying precisely where and why farmers drop off in understanding of CSA practices, this study enables more efficient allocation of scarce extension resources and more effective support for farmers building the knowledge they need to enhance resilience to climate change. The findings have immediate applicability for extension policymakers, and farming systems across Africa and beyond. As Vincent et al. (2018) and Singh et al. (2018) emphasize, multi-stakeholder partnerships that co-create solutions ensure climate information is not just available but usable, timely, and trusted. Similar insights Bashiru et al. (2024), Kesby (2005), and Rosenstock et al. (2016) collectively form the importance of participatory approaches – which center farmer knowledge, enable co-creation, address systemic inequalities – are essential for overcoming adoption barriers and achieving equitable, scalable outcomes in agricultural development.

1.8 Objectives

This study specifically aims to (1) assess farmers' levels of awareness, knowledge, and understanding of principles for 13 CSA practices; (2) compare these three levels to identify patterns of alignment and mismatch; (3) examine variation in awareness, knowledge, and principles by gender and education levels (4) analyze the progression of farmers through the three levels of understanding.

2 MATERIALS AND METHODS

2.1 Study area

The study was conducted in Zavala district, Inhambane province, located in southern Mozambique along the Indian Ocean coastline. Zavala district lies between latitudes 24°30′ and 25°00′S and longitude 34°45′ and 35°15′E, covering an area of approximately 3500square kilometers. The district is administratively divided into two administrative posts: Zavala-sede, Zandamela, which is further sub-divided into four localities (Quissico, Muane,

Zandamela, and Maculuva) with 64 villages. The region is characterised by tropical coastal climate with distinct wet and dry seasons. The wet season extends from November to March, receiving average annual rainfall between 800 and 1200 millimeters, with coastal areas receiving higher precipitation due to oceanic influence. The dry season spans April to October with average temperatures ranging from 20°C during cooler months to over 30°C in warmer months. The topography consists primarily of coastal plains interspersed with sandy, low-fertility soils and small hills, these agro-ecological conditions create vulnerability to both drought and occasional floods, with the region experiencing increasing frequency of extreme weather events in recent decades.

Agriculture is the primary economic activity, with approximately 85 percent of the population engaged in farming. The farming system is predominantly rain-fed smallholder agriculture, with an estimated 30,000 farmers averaging 3.2 hectares per household. Major crops include cassava, maize, groundnuts, and fruit varieties such as mangoes, oranges and coconuts. Livestock rearing, primarily poultry, goats, cattle, and pigs complement crop production. However, poor soil fertility, limited access to modern agricultural inputs, inadequate infrastructure, and market constraints significantly challenge productivity.

The district has been the focus of numerous climate-smart agriculture interventions by governmental and non-governmental organizations. The ministry of agriculture has established climate-smart agriculture cooperatives to promote drought-tolerant seeds, and drip irrigation. The food and agricultural organization (FAO) has supported ecological training hubs utilizing model farmers to demonstrate soil conservation practices and the private-sector initiatives have introduced water-index insurance program. Green Future Zavala has implemented women-led solar irrigation projects; the community seed banks supported by the ministry of environment and CGIAR encourage biodiversity conservation. The united development programme has facilitated farmer field schools on flood adaptation, and CARE international has supported collective farming practices and savings groups. This concentration of diverse CSA interventions made Zavala District a suitable context for assessing farmers' awareness, knowledge, and understanding of climate-smart agricultural practices. However, because Zavala was purposively selected for its concentration of CSA interventions, the absolute awareness figures reported in this study are likely higher than the average Mozambican district, and findings should be generalised only to contexts with similar intervention intensity

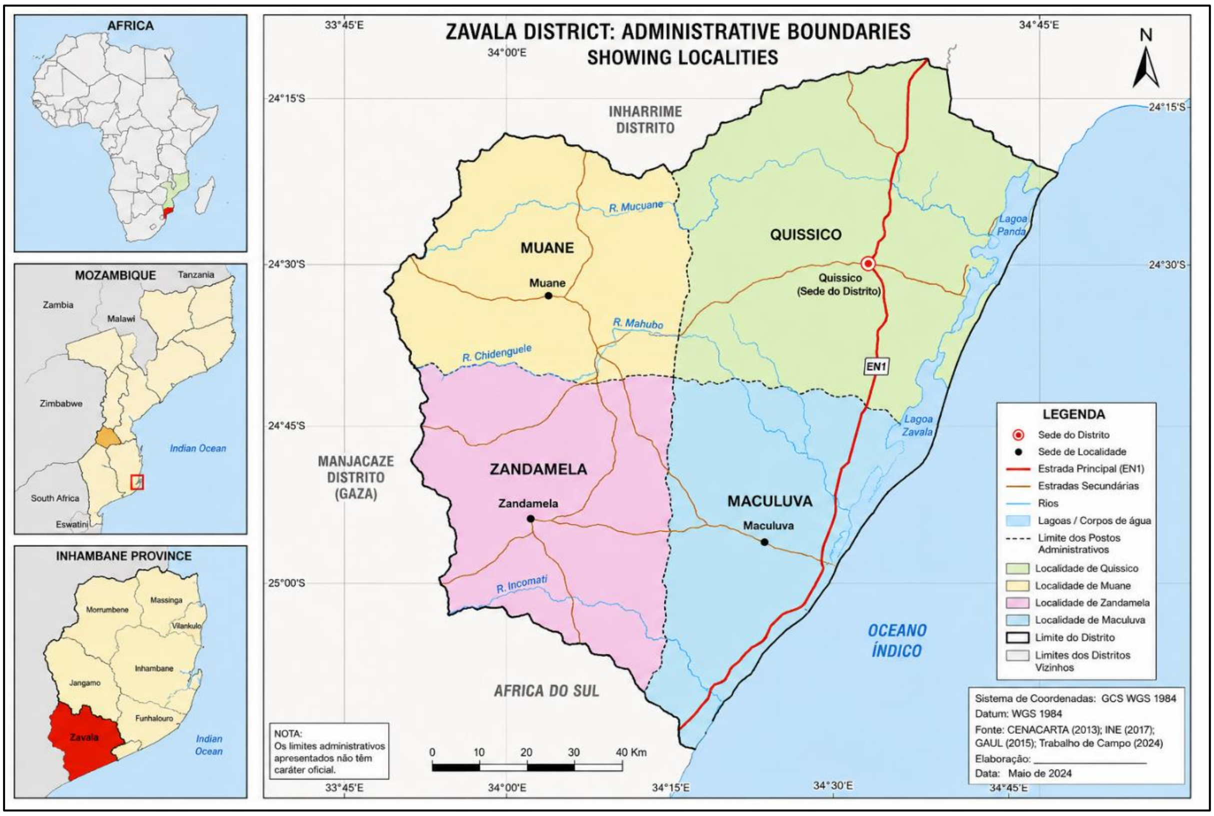

Figure 5: Study site map

2.2 Sampling determination

The target population of this study comprised smallholder farers in Zavala District who have been engaged in agricultural production for at least three years. Smallholder farmers defined in this study as those cultivating less than two hectares of land, which is the typical farm size in the district and potentially exposed to climate vulnerabilities. The sampling frame was developed from the village register maintained by the agricultural extension offices. These registers list approximately 30,000 farmers across the district, providing a comprehensive sampling frame. The register include information on household heads, farm size, and location, enabling stratified sampling. The study used Cochran (1977) sample size determination formula for cross-sectional studies estimating a proportion

$$\mathbf{n_0} = \frac{\mathbf{Z^2 p(1-p)}}{\mathbf{e^2}}$$

Where Z = 1.96 (for 95% confidence level),
P = 0.5 (maximum variability, as non-prior estimate of CSA awareness in Zavala available),
E = 0.05 (desired margin of error)
Finite population adjustment

$$\mathbf{n} = \frac{\mathbf{n_0}}{\mathbf{1} + \frac{\mathbf{n_0 - 1}}{\mathbf{N}}}$$

Assuming a 95% confidence level (Z = 1.96), 5 % margin of error (e = 0.05) and proportion p = 0.5, the initial sample size was 384. Applying the finite population correction for N = 30,000 resulted in a final sample size of 379 respondents, which was rounded up to 400 to account for potential non-responses, incomplete questionnaires, and data entry errors and it also served to improve the reliability of the result. Increasing sample size beyond the minimum recommended threshold is consistent with best practices in social science research because it enhances statistical power and improves the representativeness of findings. This 400 smallholder farmers selected represented a sample size sufficient for subgroup analyses (e.g. gender, education) and for detecting medium-size effects (Cohen's d ≥ 0.3) with power > 0.80 at $\alpha = 0.05$.

2.3 Sampling procedures

A multistage sampling technique was used to obtain the required number of respondents. Multistage sampling was appropriate because the study population is geographically dispersed across several administrative posts, localities, villages, and households. The use of multiple sampling stages helped to ensure adequate representation of different socio-economic and agro-ecological conditions within the district while reducing the logistical costs of data collection.

Stage 1: Zavala district was selected due to its high dependence on smallholder agriculture and its vulnerability to climate variabilities, besides; the district has had CSA interventions promoted in the area. It also has experienced climate-related challenges affecting agricultural productivities, making it a suitable case study for investigating climate-smart agricultural adoption decisions. Caution in generalizing absolute awareness levels to less intervention-dense areas is noted in the limitations

Stage 2: Both administrative posts in the district, namely Quissico and Zandamela, were included in the study to ensure broad geographical coverage. Including the district's two administrative pots minimized sampling bias and allowed the study to capture potential variations in farming practices and climate adaptation strategies across the district.

Stage 3: All the four localities in the district were included. The inclusion of Quissico, Muane, Zandamela, and Maculuva localities ensured representation of diverse farming environments and household characteristics. These localities served as the primary sampling units for the selection of villages.

Stage 4: Villages were selected from each locality using simple random sampling. The number of villages selected from each locality was determined proportionally based on the estimated distribution of villages across the district. Out of approximately sixty-four (64) villages in the district, 32 villages were selected for the study, representing about 50 percent of the total villages. Proportionate sampling ensured that localities with more villages contribute more respondents to the final sample, thereby improving representativeness.

Stage 5: The study conducted a systematic random sampling of households within each village. households were listed in alphabetical order and a sampling interval *k* was calculated as

$$k = \frac{N\text{village}}{n\text{village}}$$

Where *N*village = total farming households in the village, and *n*village was allocated proportionally to the village's share of district farming population (probability proportional to size). A random start between 1 and *k* was selected, and every *k-th* household was chosen. If a selected household was not available after three visits, the next household on the list was substituted practicing smallholder farming were selected from each sampled village. On average, 12 to 14 smallholder farmers were interviewed per village resulting in 400 respondents across the 32 villages. The distribution ensured balanced representation of farmers across administrative posts and localities.

Overall, the sampling procedure ensured that the study achieved adequate statistical representation of smallholder farmers in Zavala District. The use of sufficiently large sample size (n = 400) improves the precision of estimates and allows generalization of findings to the wider population of smallholder farmers in the district. The multistage sampling approach also ensured that variation in farmers' knowledge, perceptions and decision-making regarding climate-smart agriculture technologies were adequately captured across different geographical locations.

2.4 Survey instruments

A structured questionnaire was developed in three steps:

1. Literature review: Questions were adapted from validated instruments used in CSA adoption studies

2. Expert review: the draft was reviewed by three agricultural extension specialists at Eduardo Mondlane university and two district extension officers

3. Pilot testing: the questionnaire was pilot-tested on 30 farmers, (not included in the main sample) in a non-selected village. Based on pilot feedback, ambiguous terms were clarified, and the average interview time was adjusted to 30-45 minutes. No major changes to the core CSA practice list were added.

2.5 Variable measurements

Dependent variables (three levels for each 13 practices)

- **Awareness (B variables):** for each practice, farmers were asked: "have you heard of [practice]?" (0 = No, 1 = Yes). No further explanation was provided at this stage.
- **Knowledge (C variables):** only farmers who answered "Yes" to awareness were asked: "Do you know how to implement [practice] on your own farm?" (0 = No, 1 = Yes). Farmers who were not aware were coded as "0" for knowledge
- **Understanding of principles (D variables):** only farmers who answered "Yes" to knowledge were asked: "Do you understand the scientific principles behind why [practice] works?" The enumerator provided a simple explanation "for example, understanding why mulching keeps soil moist, not just how to speared mulch" (0 = No, 1 = Yes).

From these, the following composite scores were constructed:

- **Total awareness score:** sum of B variables across 13 practices (range 0-13)
- **Total knowledge score:** sum of C variables across 13 practices (range 0-13)
- **Total principles score:** sum of D variables across 13 practices (range 0-13),

For each of the thirteen practices, separate binary indicators were creates for awareness, knowledge and understanding principles yielding

- Progression score (per practice): 0 = no awareness; 1 = aware only (B=1, C=0, D=0); 2 = aware and knowledgeable (B=1, C=1, D=0); 3 = aware, knowledgeable and understands principles (B=1, C=1, D=1).

A total progression score was then calculated as the sum across all practices, with a maximum possible score of 39

- Total progression score = sum of progression scores across 13 practices (range 0-39).
- Composite "true familiarity": For each practice, TRUE = 1 if Awareness = 1 OR Knowledge = 1 was constructed (i.e., farmer has either heard of a practice **or knows how to implement a practice). This addresses terminology mismatch.**

Independent variables (socio-demographic and institutional)

- Gender: 1 – male, 2 – female (recorded by observation or self-report)
- Education level: categorical = 0 = no formal education, 1 = primary school(complete o incomplete), 2 = secondary school, 3 = tertiary/ university
- Age: continuous (years, self-reported)
- Farming experience: continuous (years of active farming)
- Household size: number of members living in the household
- Group membership: 0 – no, 1 = yes (member of any farmer cooperative, savings group, or CSA group)
- Extension access: 0 = no contact with extension agent in the past 12 months, 1 = at least one contact

2.6 Data collection

Data were collected over a period of six weeks from August to mid-September through face-to-face interviews. A team of six enumerators was trained over five days in questionnaire administration, ethical protocols, and data collection procedures (Creswell, 2014). Interviews were conducted in the preferred language of respondents and each interview lasted approximately thirty to forty-five minutes. Quality control measures included daily debriefing sessions, random spot checks by supervisors, and daily review of completed questionnaires for completeness and consistency.

2.7 Data analysis

Data analysis for this study was conducted using IBM SPSS Statistics version 26, following a systematic and sequential approach that progressed from simple descriptive summaries to increasingly complex inferential models. Data were cleaned and screened for errors, missing values and violations of statistical assumptions. The sample size provided sufficient statistical power for all planned analyses, including subgroup comparisons and cumulative modeling. All statistical tests were two-tailed with a significance level set at $\alpha = 0.05$ and effect size were calculated or all parametric tests to provide information about practical significance beyond mere statistical significance.

Phase One: Descriptive Statistics

The analysis proceeded through eleven interconnected phases. **First, descriptive statistics** including means, standard deviations, frequencies, percentages and ninety-five percent confidence intervals using Wilson score method were computed to characterize the sample and establish baseline distributions.

Phase Two: Comparative Analysis for Hypothesis Testing

To test the hypothesis that female farmers have significant higher awareness, knowledge and understanding of principle scores compared to male farmers, **comparative analyses using independent sample t-tests** were conducted with Levene's test for equal variance found to be significant. Welch's correction was used to modify the degree of freedom downwards to account for unequal variance in controlling type 1 error. Since principles scores showed mild skewness in their distribution, **Mann-Whitney U tests** was performed as a non-parametric alternative in combining all observations from both groups into a single ranked list. The Mann-Whitney U tests was reported alongside the t-test results to provide converging evidence for gender comparison.

To test the hypothesis that education level is positively associated with higher awareness, knowledge and understanding of principles scores, **one-way analysis of variance** (ANOVA) as conducted. The independent variables was education ith four categories no formal education (coded as 0), primary education (coded as1), secondary education (coded as 2), and tertiary/university education (coded as 3). The dependent variables were total awareness, total knowledge and total understanding of principles. A large F-statistics indicated that the between-group variance is large relative to within-group variance suggesting that group mean are not equal. Eta-squared was calculated as the effect size measure for the ANOVA, to represent proportion of total variance in the dependent variable that is attributable to education level. Since one-way ANOVA was significant at $p < 0.05$, Tukey's Honestly Significance Difference post-hoc tests was conducted to identify which specific pair of education differs significantly. For each education level, absolute difference between the two means were calculated and compared to the HSD critical value. Violation of homogeneity of variance by some independent variables prompted the use of Welch's ANOVA and Kruskal-Wallis tests as non-parametric alternatives and were reported to confirm the findings from the standard ANOVA.

Phase Three: Bivariate Association Analysis

The relationship between total awareness and total knowledge were examined using Pearson correlation coefficient to measure strength and direction of the linear relationship between two continuous variables, the coefficients ranged from negative to positive. The negative indicates a perfect negative linear relationship, zero indicates no linear relationship while positive indicates a perfect positive linear relationship Pearson correlation coefficient was computed by calculating the variance between two variables. The significance of the correlation coefficient was tested using a t-test with degree of freedom equal to the sample size minus two. The relationships involving total principles were examined using Spearman rank correlation coefficient, a non-parametric measure that assesses monotonic relationships. The correlation strength was interpreted using standard guideline (absolute value less than 0.3 considered weak, values between 0.3 and 0.7 wee considered moderate, and values greater than 0.7 were considered strong). Both Pearson and Spearman correlations were reported, with Pearson correlation used for the awareness-knowledge relationship and the Spearman correlation used for relationships involving principles. To assess the association between categorical variables, chi-square tests of independence were conducted to evaluate whether observed frequencies in the contingency table differ from the frequencies that would be expected under the null hypothesis of independence between the two categorical variables. A contingency table was created for each cross-tabulation showing observed frequencies of each combination of categories the expected frequency for each was calculated and the chi-square statistic computed. A statistically significant chi-square statistic ($p < 0.05$) indicated that the two variables were associated. Cramér's V was calculated as an effect size measure for the chi-square tests, the Cramér's V ranges from zero to one with values close to one indicating strong association.

Phase Four: Factor Analysis of Rogers' Perceived Attributes

To test the hypothesis that Rogers' five perceived attributes are empirically distinguishable dimensions in Zavala smallholder context, the five attributes examined were relative advantage, compatibility, complexity (reversed), trialability and observability **Principal component extraction method was used**. Each attribute was measured on a five-point Linkert scale. Two distinctive tests were performed: The Keiser-Meyer-Olkin measure of sampling adequacy was calculated to asses whether variables shared sufficient common variance.

Bartlett's test of sphericity was calculated to test the null hypothesis that correlation matrix is an identity matrix based on the determinant of the correlation matrix and follows chi-square distribution. **Principal component extraction** method was then applied to transform the original variables into smaller sets of uncorrelated components to capture maximum possible variance. Eigenvalues were computed for each component. The Keiser correlation, which retains components with eigenvalues greater than one was used to determine the number of components to retain. Factor loading (correlation between each original variable and the extracted component) were examined to integrate the component structure. Loading with components greater than 0.4 were considered meaningful

Phase Five: Composite Measures for Terminology Mismatch

To address the terminology mismatch phenomenon, identified as the "improved varieties paradox," **composite measures** were conducted. For each CSA practice, a binary variable called "true familiarity" was identified. This variable took the value one if the farmers had either heard of the practice (aware) or know how to implement it (knowledge), and zero if the farmer had neither awareness or knowledge. This composite measure captures whether a farmer possesses any form of familiarity with the practice, regardless of whether that familiarity is captured by formal terminology used in the survey. The composite percentage was then calculated as the number of farmers with true familiarity divided by the total sample size and multiplied by one hundred. The composite percentages was compared with the original awareness percentages to identify practices where knowledge substantially exceeded awareness. The increase from the original awareness percentage to the composite percentage was calculated as the difference between the composite percentage and the original awareness percentage. A large positive increase indicated that many farmers possess knowledge of practice without recognizing the formal terminology.

Phase Six: Progression Analysis

Progression analysis: for each of the thirteen CSA practices, a progression score was assigned to each farmer based on their responses to the three levels of understanding. This score operationalized he theoretical hierarchy rom Bloom's taxonomy. Farmers who reported no awareness of practice were assigned a progression score zero. Farmers who reported awareness but not knowledge were assigned a score of one. Farmers who reported both awareness and knowledge but did not understand the underlying principles were assigned a score two. Farmers who reported awareness, knowledge and understanding of principles were assigned a score of three. A total progression as then calculated for each farmer by summing the progression scores across the thirteen practices. This total progression score had a potential range from zero to thirty-nine, where zero would indicate no awareness of any practice and thirty-nine would indicate full understanding of all the thirteen practices at all three levels. The **frequencies and percentages** of farmers at each progression level were tabulated for each individual practice. This allowed visualization of the “funnel” pattern from awareness-knowledge-principles. Showing how many farmers progressed through each stage and where the major bottleneck occurred. The distribution of total progression was summarized with means, medians, standard deviations and percentiles to describe the overall cognitive development of the sample.

Phase Seven: Multiple Linear Regression Analysis

To identify factors associated with total awareness total knowledge, and total understanding of principles scores, **multiple linear regression using enter method** was used. For each of the three dependent variables, the same set of independent variables (age in years, gender coded as dummy variables with female as te reference category, education level coded ordinally from zero to three, farming experience in years, and annual income) were ended simultaneously. The enter method was chosen because there was no theoretical basis for prioritizing predictors or using stepwise selection. Several assumptions were checked including normality o residual using Shapiro-Wilk and visual inspection of Q-Q plots. Homoscedasticity (variance of the residuals is constant across all levels of predicted values), independence of errors was assumed using the Durbin-Watson statistics, and multicolinearity was examined using Variance Inflation factor. For each regression model, standardized coefficients (B) were calculated, the coefficient of determination R^2 was calculated to indicate the proportion of variance in independent variable explained by set of predictors. The adjusted R^2 was reported and F-tests conducted to tests the null hypothesis that all regression coefficients were simultaneously equal to zero, indicating linear relationship between the predictors and the dependent variable. F-statistic was calculated as the ratio of the regression mean square to residual mean square and was compared to the F-distribution with degree of freedom equal to the number of the predictors.

Phase Eight: Multinomial Logistic Regression

To identify factors differentiating farmers among low, moderate, and high adoption levels, **multinomial logistic regression** was employed. The dependent variable was adoption level, with three categories: low adoption, moderate adoption, and high adoption. Low adoption was designated as the reference category (the model estimated the log odds of being a moderate or high adopter relative to low adopter). The dependent variables included age on years (continuous), farming experience in years (continuous) gender (dummy coded with female as reference), extension contact (dummy coded with no contact as reference) and cooperative membership (dummy coded with non-member as reference). All independent variables were entered simultaneously and the model was estimated using maximum likelihood. For each predictor, a coefficient (β) was estimated to represent that change in log odds of being in a higher adoption category (relative to low adoption) for one-unit change in the predictor. Positive coefficients indicated increase in the predictor are associated with increased odds of being in higher adoption category, while negative coefficients indicate decreases odds. Standard errors were captured for each coefficient and used to calculate Wald statistics fort testing significance of individual coefficient, odds ratios were calculated by exponentiation the coefficients with odd ration greater than one indicating increased odd. Coefficient for odds ratios were captured at ninety-five percent confidence level. Overall model fit was assessed using likelihood ratio chi-square tests. The Pseudo R^2 measures including Cox and Snell R^2 and Nagelkerke R^2 were reported as approximate indicators of the model fit.

Phase Nine: Robustness Checks with Ordered Logistic and Tobit Regression

Since the progression scores were ordinal and bound, robustness checks were performed using alternative models to ensure that the findings were not artifact of the specific modeling choices. **Ordered logistic regression** was conducted for practice-level progression, with the dependent variable being progression level (zero, one, two, or three). The proportional odds assumption was tested using Brant tests with non-significant results indicating proportional odds assumption reasonable. Positive coefficient indicated higher values of the predictors are associated with higher progression levels. For total progression score bounded at zero to thirty-nine, Tobit regression was used. The total progression score could not fall below zero and beyond thirty-nine creating floor and ceiling effects. The Tobit model assumed that there is latent variable Y* that is nearly related to the predictor but the observed Y is censored at the lower bound of zero and the upper bound of thirty-nine. Both the ordered logistics and Tobit regression models were estimated with the set of independent variables as the linear regression model the coefficients, standard errors, and significance levels were compared to those from the linear regression models to confirm that the direction and significance of effect were consistent across molding approaches.

2.8 Ethical considerations

An ethical exemption letter was obtained from the Institutional Review Board of Eduardo Mondlane University. Additionally, GUIA DE MARCHA was obtained and assented to by the district agricultural officer. Informed verbal consent was obtained from all respondents prior to interviews, overseen by the district agricultural office (SDAE) of Zavala. The respondents were informed of the right to withdraw at any time without consequences. Data collection prioritized confidentiality through anonymized identification numbers. Interviews were conducted in private settings, with female respondents preferably assigned to female enumerators. No monetary compensation was provided during the entire process of data collection, and results will be disseminated through academic publications and community feedback sessions.

RESULTS

3.1 Socio-demographic characteristic of respondents

Table 1 shows the sample composing of 400 farmers, with 265 male (66.3%) and 135 female (33.8%). Education varied across the age groups with 1.8% having no formal education, 42.3% representing respondents with primary education, 24.8% of farmers had secondary education and 31.3% attained tertiary/university education. Mean farming experience was 22.5 years (SD = 10.3). Mean age was 45.3 years (SD = 8.7), mean farm size of 3.2 hectares (SD = 1.5).

Table 1: Socio-demographic characteristics of respondents (n = 400)

Characteristics	Category	n	%
Gender	Male	265	66.3
	Female	135	33.8
Education Level			
	No formal education	7	1.8
	Primary school	169	42.3
	Secondary school	99	24.8
	Tertiary/University	125	31.3
Farming Experience (years)	Mean ± SD		22.5 ± 10.3
Farm Size (hectares)	Mean ± SD		3.2 ± 1.5

3.2 Results of farmers' awareness, knowledge, and understanding of CSA technology

***Specific objective1**: Assessment of farmers' awareness, knowledge and understanding o of principles associated with CSA technologies*

3.2.1 Awareness, knowledge, and principles across practices

Hypothesis H1a tested whether there is a statistically significant difference between awareness levels and knowledge levels across the 13 CSA practices.

Paired t-tests were conducted for each of the 13 practices, comparing the percentage of farmers aware of the practice with the percentage who knew how to implement it. This approach accounts for the fact that awareness and knowledge scores came from the same farmer for each practice.

Results showed that a significant difference ($p < 0.05$) was found for five practices. Rainwater harvesting showed the largest gap (81% aware vs. 39% knowledge, gap = -42 percentage points, $p < 0.001$). Agroforestry followed (90% vs 66%, gap = -24.3 percentage points, $p < 0.001$). Biofertilizers (65% vs 54%, gap = -10.5 percentage points, $p < 0.001$). For soil fertility management, knowledge exceeded awareness (65% vs 56%, gap = +9.0 percentage points, $p < 0.05$). For improved varieties, knowledge also exceeded awareness (67% vs 47%, gap = +20.0 percentage points, $p < 0.001$). The remaining eight practices (intercropping, crop rotation, drought-tolerant crops, IPM, organic farming, conservation tillage, cover cropping, water-efficient irrigation) showed no significant difference ($p > 0.05$), as shown in Table 2 below.

Table 2: Comparison of awareness, knowledge, and understanding of principles across CSA practices

Practice	Awareness (%)	LL	UL	Knowledge (%)	LL	UL	Principles (%)	LL	UL	Gap (pp)	Pattern
Intercropping	100.0	99.1	100.0	99.0	97.5	99.7	39.8	35.0	44.7	-1.0	Aligned
Crop Rotation	90.8	87.6	93.4	91.0	87.9	93.6	81.5	77.4	85.1	+0.2	Aligned
Agroforestry	90.3	87.0	93.0	66.0	61.3	70.5	65.5	60.8	70.0	-24.3	Awareness > Knowledge
Rainwater Harvesting	81.0	76.9	84.7	39.0	34.3	43.9	27.0	22.8	31.6	-42.0	Awareness > Knowledge
Drought-Tolerant Crops	65.8	61.0	70.3	66.0	61.3	70.5	65.5	60.8	70.0	+0.2	Aligned
Integrated Pest	65.8	61.0	70.3	65.5	60.8	70.0	33.5	29.0	38.3	-0.3	Aligned

Management											
Biofertilizers	64.5	59.7	69.1	54.0	49.1	58.8	62.0	57.2	66.6	-10.5	Awareness > Knowledge
Soil Fertility Management	56.0	51.1	60.8	65.0	60.3	69.5	47.0	42.1	51.9	+9.0	Knowledge > Awareness
Organic Farming	55.3	50.4	60.1	54.0	49.1	58.8	59.4	54.5	64.1	-1.3	Aligned
Conservation Tillage	54.3	49.4	59.1	54.0	49.1	58.8	83.5	79.6	86.9	-0.3	Aligned
Cover Cropping	53.5	48.6	58.3	55.0	50.1	59.8	66.5	61.8	70.9	+1.5	Aligned
Water-Efficient Irrigation	53.5	48.6	58.3	54.0	49.1	58.8	39.8	35.0	44.7	+0.5	Aligned
Improved Varieties	47.0	42.2	51.9	67.0	62.3	71.4	81.8	77.7	85.4	+20.0	Knowledge > Awareness

Note: LL = Lower Limit (95% confidence interval lower bound); UL = Upper Limit (95% confidence interval upper bound) negative gaps indicate awareness exceeds knowledge; positive gaps indicate knowledge exceeds awareness.

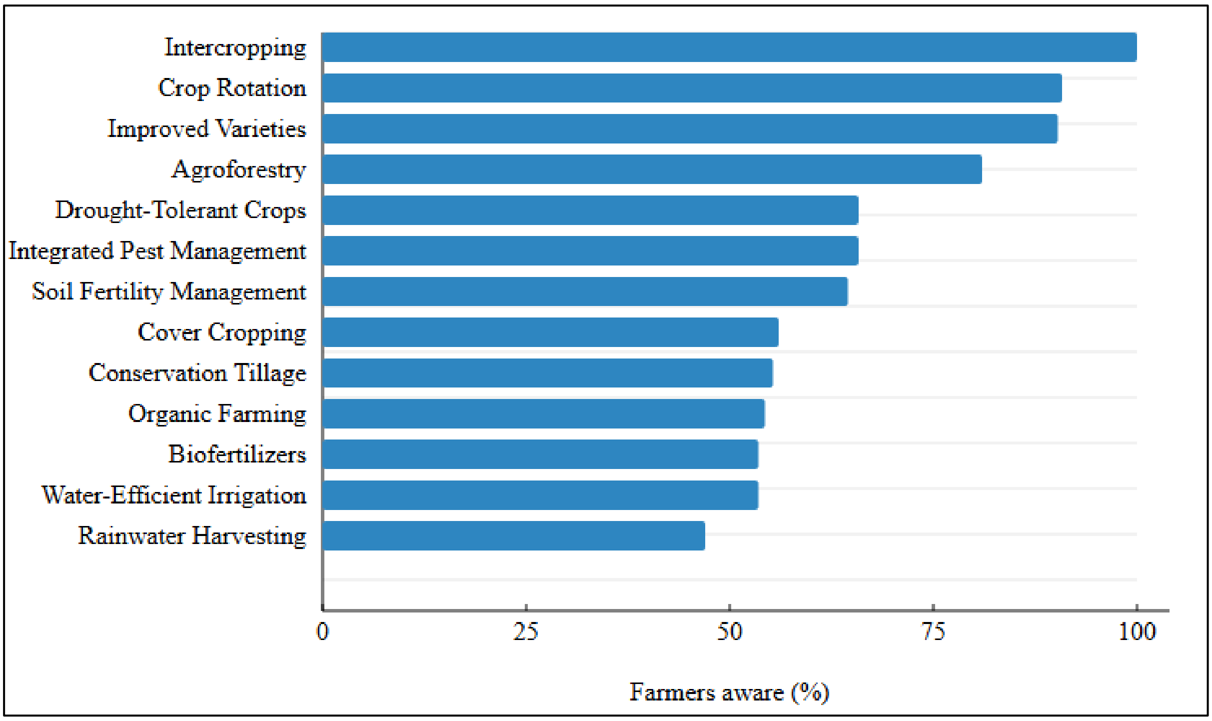

Figure 6: Farmers' awareness of climate-smart agriculture practices

Decision: we reject the null hypothesis (H_0) for five practices with significant gaps. For the eight aligned practices, we fail to reject (H_0). Overall, awareness and knowledge are not always equal.

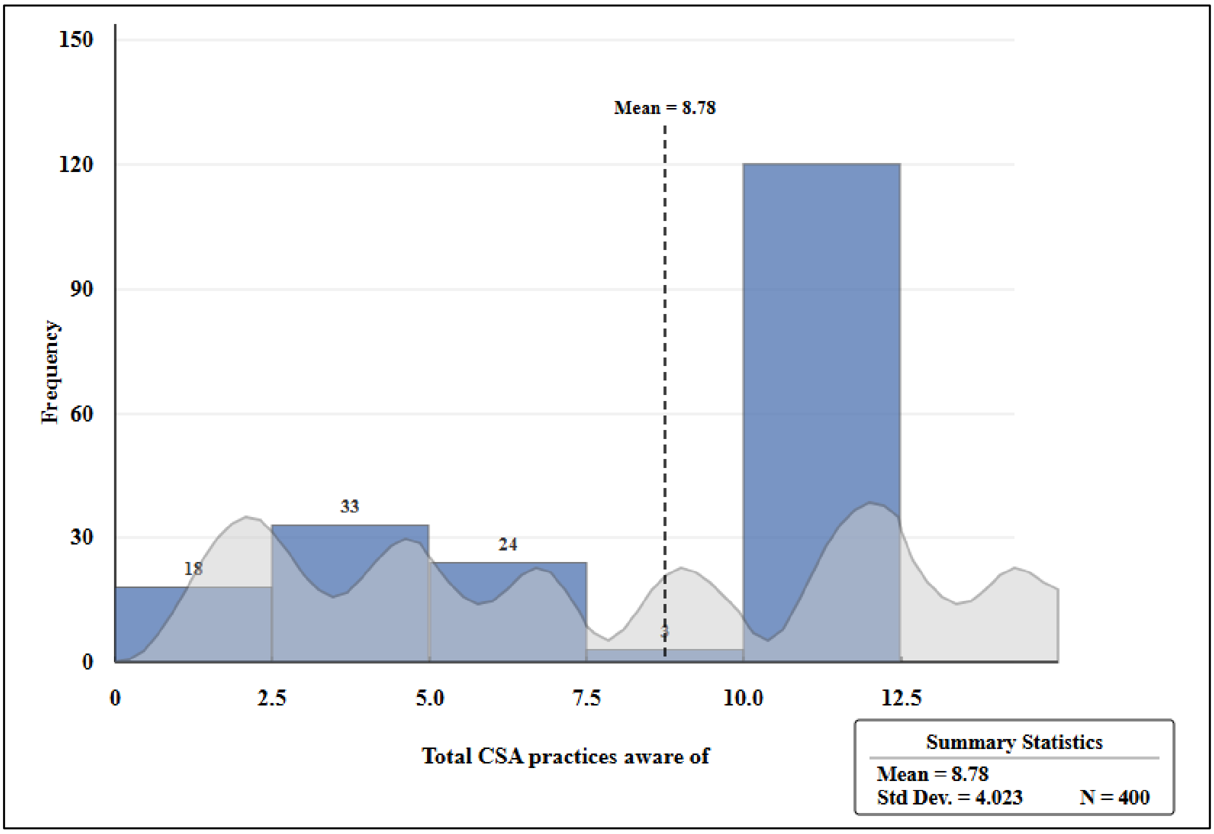

Figure 7: Bimodal CSA practices awareness distribution

Interpretation: Three patterns emerged. Pattern 1 (awareness > knowledge) indicates superficial awareness requiring skills training. Pattern 2 (knowledge > awareness) shows terminology mismatch where farmers possess practical knowledge but do not recognize formal terms. Pattern 3 (aligned) demonstrating that extension programs must adopt stage-specific approaches based on which pattern a practice exhibits.

3.2.2 Gender differences in awareness, knowledge, and principles

Hypothesis H1b tested whether female farmers have significantly higher awareness, knowledge, and understanding of principles scores compared to male farmers.

Independent sample t-tests were conducted to compare mean total awareness, total knowledge and total principles scores between male (n = 256) and female (n = 135) farmers. Since principles, score showed mild skewness, Spearman *p* test were performed as non-parametric alternatives.

Table 3 shows results for total awareness, female (M = 11.34, SD = 2.20) scored significantly higher than males (M = 7.47, SD = 4.11); t (398) = -10.215, p < 0.001; Mann-Whitney U: Z = -8.427, p < 0.001. For total knowledge, females (M = 10.21, SD = 2.45) vs. males (M = 6.82, SD = 3.95); t = -9.896, $p < 0.001$; Z = -7.974, $p < 0.001$. For total principles, females (M = 9.45, SD = 2.62) vs males (M = 6.24, SD = 3.78); t = -9.23, $p < 0.001$; Z = -2.250, $p < 0.024$

Table 3: Awareness, knowledge, and understanding of principles by gender

Variable	Male (n=265)	Female (n=135)	t-value	p-value
Total Awareness	7.47 ± 4.11	11.34 ± 2.20	-10.215	<0.001
Total Knowledge	6.82 ± 3.95	10.21 ± 2.45	-9.896	<0.001
Total Principles	6.24 ± 3.78	9.45 ± 2.62	-9.23	<0.001

Values are mean ± standard deviation. All differences are statistically significant at p < 0.001.

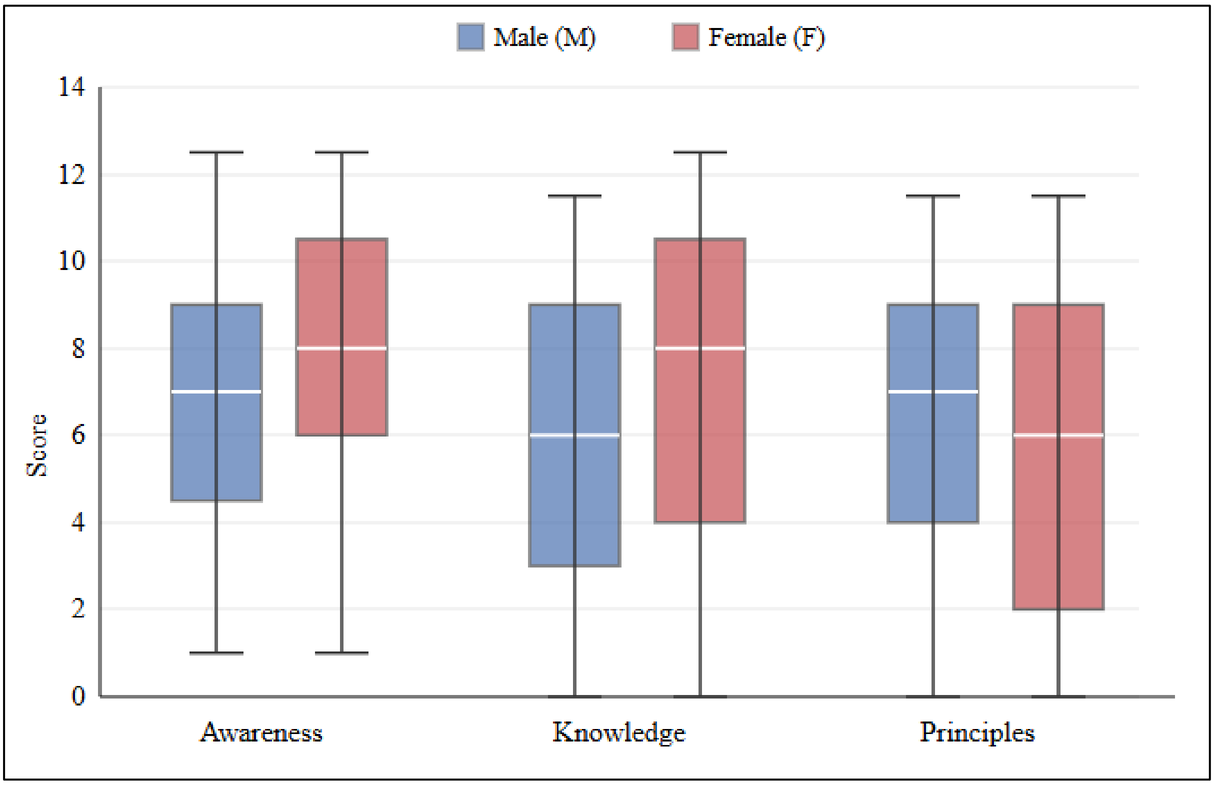

Figure 8: Boxplot of awareness, knowledge, and understanding of principles by gender

Decision: We reject the null hypothesis (H_0) for all three measures. The alternative hypothesis (H_1) is supported.

Interpretation: the independent sample t-test results suggests that female farmers possess greater awareness, knowledge, an understanding of principles of climate-smart agriculture practices than their male counterparts do. The result may reflect differences in participation in agricultural training programmes, exposure to climate adaptation initiatives, or engagement in farming activities that promote learning and application of climate-smart agricultural practices. Consequently, gender appears to be an important factor influencing farmers' capacity to acquire and utilize climate-smart agriculture knowledge.

3.2.3 Education differences in awareness, knowledge and principles

Hypothesis H1c tested whether education level is positively associated with higher awareness, knowledge, and understanding of principles scores

One-way analysis of variance (ANOVA) was conducted to compare means across four education levels: no formal education (n = 7), primary education (n = 169), secondary education (n = 99), and tertiary/university education (n = 125). Where ANOVA indicated significant differences ($p < 0.05$), post-hoc comparisons were performed using Tukey's Honestly Significant Difference (HSD) test.

Results for total awareness: ANOVA revealed a significant effect ($F = 748.78$, $p < 0.001$, $\eta^2 = 0.85$). Post-hoc tests showed that farmers with secondary education (11.60 practices) had significantly higher awareness than those with primary education (4.67 practices, $p < 0.001$). Farmers with tertiary education (12.40 practices) were also significantly higher than secondary ($p < 0.05$). For total knowledge, similar results were found ($F = 933.06$, $p < 0.001$), with secondary (11.10 practices) and tertiary (12.73 practices) far exceeding primary (3.60 practices). For total principles, the effect was smaller but still significant ($F = 4.16$, $p < 0.006$). Post-hoc tests indicated that only the difference between no formal education (5.57 practices) and primary education (7.18 practices) was significant ($p < 0.05$); secondary and tertiary education did not differ significantly from primary for principles. This is shown in Table 4.

Table 4: Education differences in awareness, knowledge, and understanding of principles

Education Level	**n**	**Total Awareness**	**Total Knowledge**	**Total Principles**
No formal education	7	3.29 ± 0.95a	1.86 ± 0.69a	5.57 ± 1.99a
Primary school	169	4.67 ± 2.13b	3.60 ± 1.96b	7.18 ± 2.37b
Secondary school	99	11.60 ± 1.20c	11.10 ± 1.78c	8.04 ± 2.55b
Tertiary/University	125	12.40 ± 0.70d	12.73 ± 0.73d	7.69 ± 2.58b
F-value		**749.78***	**933.06***	**4.16****

p-value	**<0.001**	**<0.001**	**0.006**
Kruskal-Wallis H	314.74	323.36	12.24
Kruskal-Wallis p	**<0.001**	**<0.001**	**0.007**
η² (eta-squared)	**0.65**	**0.70**	**0.03**
ω² (omega-squared)	**0.65**	**0.70**	**0.03**

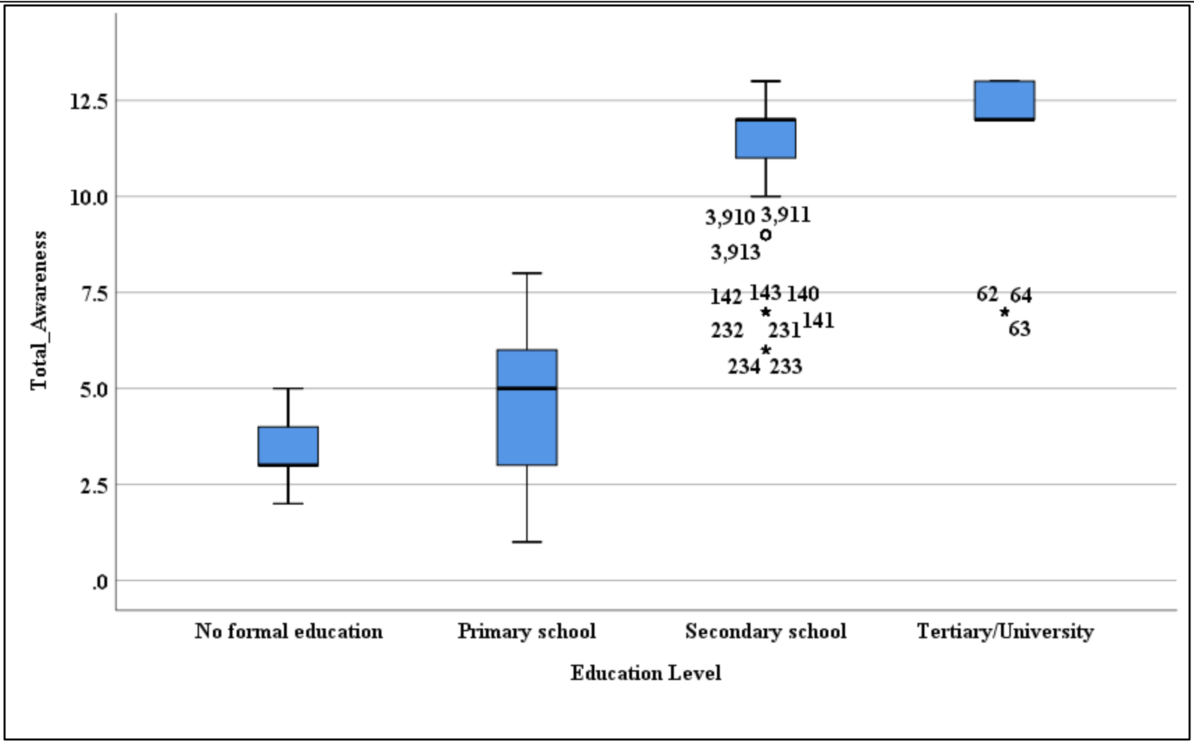

Figure 9: Boxplot for farmers' awareness by education level

Note: *dramatic increase in mean awareness score between primary and secondary education is associated with strong threshold effect; low and overlapping distributions indicates limited gains in awareness at early education stage (no formal and primary education); the marginal increase in awareness at tertiary education suggests diminishing returns beyond secondary level. Reduced variability at higher education levels (tighter distributions) indicate more consistent awareness among more educated farmers; strong separation aligns with highly significant results (ANOVA p < 0.001; Kruskal-Wallis p < 0.001) reinforcing education as key associated factor of CSA practice awareness.*

Decision: we reject the null hypothesis that education is positively associated with all three measures, though the effect on principles is weaker.

Interpretation: These findings suggest that education, particularly at the secondary level, is a critical threshold for CSA awareness and knowledge. The very large effect size ($\eta^2 = 0.65$) indicates that approximately 65% of the variation in awareness score is explained by education level, demonstrating a substantial practical impact. Whereas 70% of the variance in knowledge scores is attributed to differences in education level, representing an exceptionally large effect size. In contrast, the small effect size ($\eta^2 = 0.03$) indicates that education explains a smaller proportion (3%) of variation in understanding CSA principles. Farmers with secondary education know nearly triple the practices of those with only primary education. However, education alone does not guarantee deep conceptual understanding (principles), suggesting that different pedagogical approaches are needed for principle-level learning which might be influenced more by experiential learning and practical exposure than by formal educational attainment alone.

3.2.4 Correlations among awareness, knowledge and principles

Hypothesis H1d tested whether awareness and knowledge strongly correlate while awareness/knowledge are weakly correlated with understanding of principles.

Pearson correlation coefficients (r) were calculated for normally distributed continuous variables (total awareness vs. total knowledge). Spearman rank correlation coefficients (ρ) were used for variables not normally distributed (total principles). Correlation strength was interpreted as weak ($|r| < 0\text{-}3$), moderate ($3 \leq |r| <7$), or strong ($|r| > 7$).

Results in Table 5 show that the correlation between total awareness and total knowledge was extremely strong (Pearson $r = 0.979$, $p < 0.001$; Spearman $\rho = 0.928$, $p < 0.001$). However, correlations with total principles were much weaker: awareness-principles ($r = 0.261$, $p < 0.001$; $\rho = 0.353$, $p < 0.001$) and knowledge-principles ($r = 0.151$, $p < 0.002$; $\rho = 0.140$, $p < 0.005$). All correlations were significantly different from zero.

Table 5: Correlation matrix of awareness, knowledge and understanding of principles across 13 CSA practices

Variable	Total Awareness	Total Knowledge	Total Principles
Total Awareness	1		
Pearson r		0.979**	0.261**

Spearman ρ	0.928**	0.353**
Total Knowledge	1	
Pearson r		0.151**
Spearman ρ		0.140**
Total Principles		1

***P < 0.01, ***p < 0.001(two-tailed).

Decision: we reject the null hypothesis. The pattern supports the alternative hypothesis that awareness and knowledge are strongly correlated, while both are weakly correlated with understanding of principles.

Interpretation: the correlation analysis revealed a significant positive association among These findings suggest that although awareness and knowledge are closely interconnected, understanding of climate-smart agriculture principles constitutes a more distinct construct that may be dependent on other factors beyond simple awareness and knowledge acquisition, such as practical experience, training, farmer field school, demonstrations and engagement with climate adaptation initiatives.

3.2.5 The improved varieties paradox: Composite measures

For improved varieties, the composite measure (awareness OR knowledge) revealed true familiarity at 82.5%, compared to awareness at 47.0% and knowledge at 67.0% – an increase of 35.5 percentage points. This confirms that low awareness is largely a terminology problem**.**

Table 6: Composite measures: true familiarity (awareness OR knowledge) of selected practices. See supplementary table S4 for full practices true familiarity

Practice	Original Awareness (%)	Original Knowledge (%)	Composite True (%)	Increase
Improved Varieties	47.0	67.0	**82.5**	**+35.5**
Soil Fertility Management	56.0	65.0	71.5	+15.5
Agroforestry	90.3	66.0	92.5	+2.2

3.2.6 Progression analysis

Table 7 presents the progression analysis for agroforestry, showing the funnel form awareness to knowledge to principles. Of the 400 farmers, the funnel indicated that 39 (9.8%) had no awareness, 98 (24.5%) knew about agroforestry but did not know how to implement the practice. 2 (0.5%) Were aware and knowledgeable on implementation of agroforestry but did not understand the principles, and 261 (65.3%) had reached the deepest level of awareness, knowledge and principles.

Table 7: Progression analysis from awareness to understanding of principles for the 13 CSA practices

Level	Description	Frequency (n)	Percent (%)
0	No awareness	39	9.8
1	Aware only	98	24.5
2	Aware + Knowledge	2	0.5
3	Aware + Knowledge + Principles	261	65.3
Total		**400**	**100.0**

Note: "Aware only" = B=1. C=0, D=0; "aware + knowledge" = B=1, C=1, D=0; "aware + knowledge + principle" = B=1, C=1, D=1

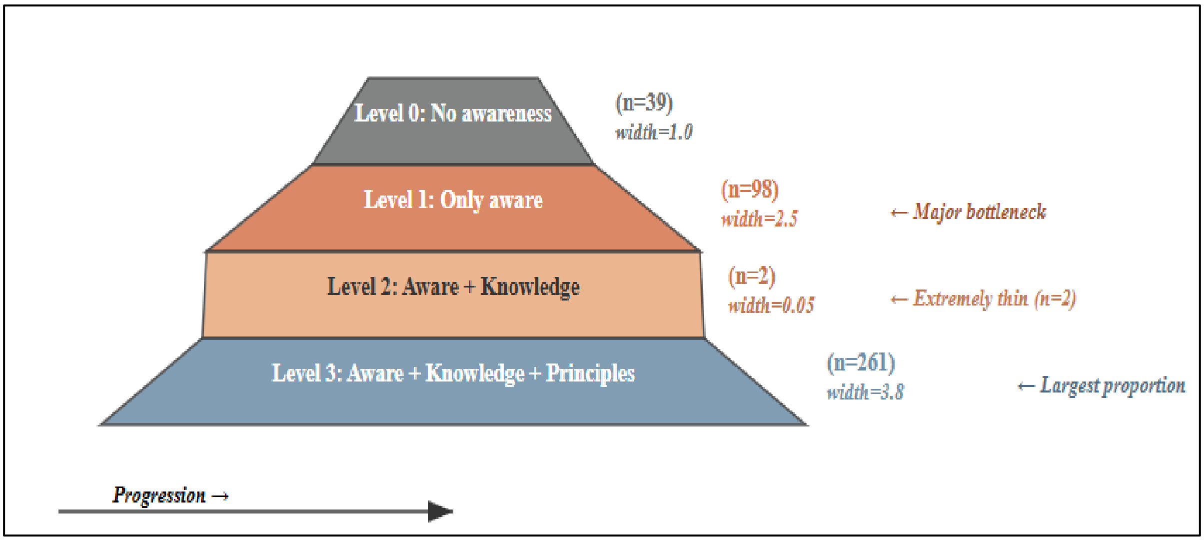

Figure 10: Agroforestry progression funnel from awareness to understanding of principles

Note: n=39 farmers have no awareness (level 0); n=98 are aware only (level 1 – major bottleneck). Only n=2 farmers are at level 2 (aware + knowledge) – an extremely thin critical transition gap. The largest portion (n=261) have reaches full understanding (level 3). Farmers tend to either remain at basic awareness or move directly to full understanding of the agroforestry practice.

3.2.7 Total progression score

Table 8 presents the distribution of total progression scores (sum of progression levels across 13 practices). The mean was 20.92 (SD = 11.77), median 25 out of a maximum possible 39. The distribution was polarized, with 28.2% of farmers scoring ≤ 10 (limited progression) and 51.2% scoring ≥ 25 (substantial progression). Figure 8 presents a histogram of total progression scores.

Table 8: Total progression score distribution for the 13 CSA practices

Statistic	Value		
N	400		
Mean	20.92		
Median	25.00		
Mode	30		
Std. Deviation	11.77		
Minimum	2		
Maximum	38		
Percentiles	25th: 10, 50th: 25, 75th: 30		
Score Range	**Frequency (n)**	**Percent (%)**	**Cumulative (%)**
2-10	113	28.2	28.2
11-24	82	20.5	48.7
25-38	205	51.2	100.0

Note: total progression sums the progression levels (0-3) across all 13 principles. Maximum = 39.

Robustness check (See supplementary table S2 & S3): Because the progression score is ordinal and bounded, we re-estimated the main model using ordered logistic regression (for practice-level progression, 0-3) and Tobit regression (for total progression score, censored at 0-39). Results were qualitatively identical: all significant predictors (gender, education, extension access) remained significant with the same direction of coefficients, and non-significant variables remained non-significant. Effect sizes from these non-linear models confirmed the pattern reported in tables 7-9. The full results are presented as supplementary table. These robustness checks increased confidence in the reporting associations.

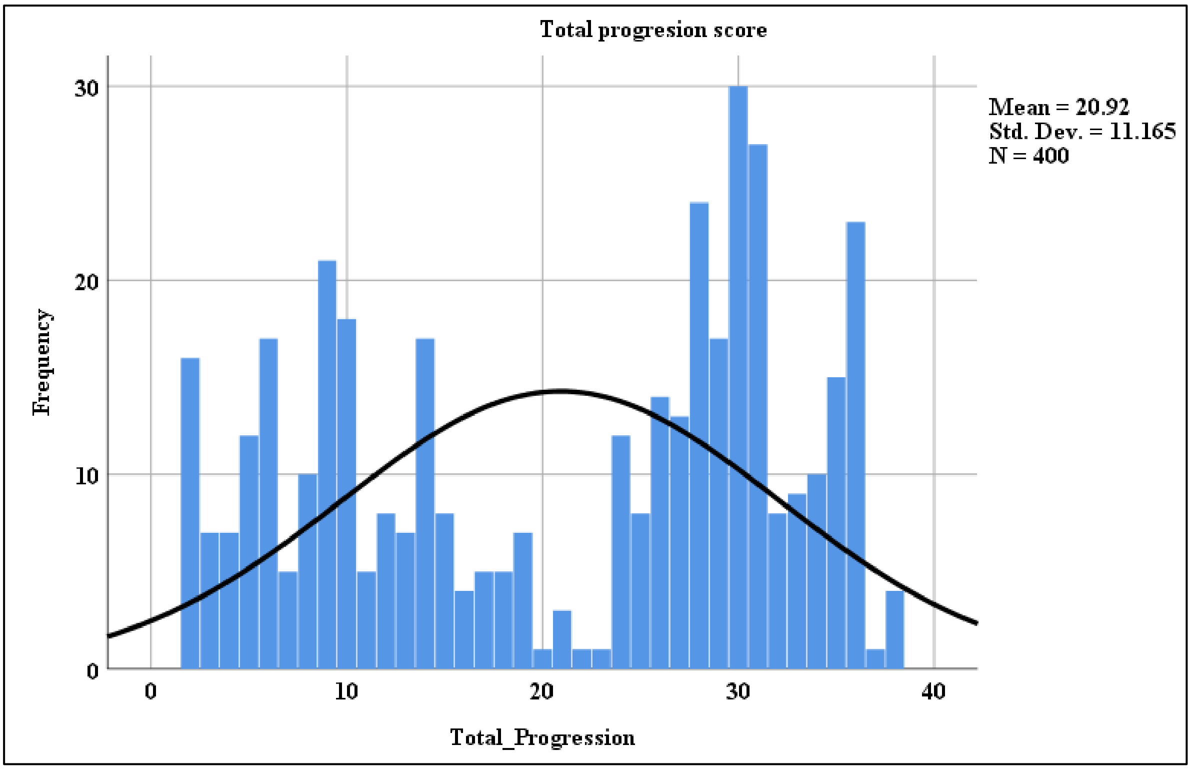

Figure 11: Histogram for total progression score across 13 CSA practices

3.2.8 Distribution of farmers by awareness level

Table 9 shows that distribution was strongly bimodal: 15.0% of farmers knew 0-3 practices (very low awareness), 19.5% knew 4-6 practices (low awareness) 11.3% knew 7-9 practices (moderate awareness), and 54.2% knew 10-13 practices (high awareness).

Table 9: Distribution of farmers by level of awareness

Awareness Level	**Number of Practices Known**	**Frequency (n)**	**Percent (%)**	**Cumulative (%)**
Very Low	0-3	60	15.0	15.0
Low	4-6	78	19.5	34.5
Moderate	7-9	45	11.3	45.8
High	10-13	217	54.2	100.0
Total		400	100.0	

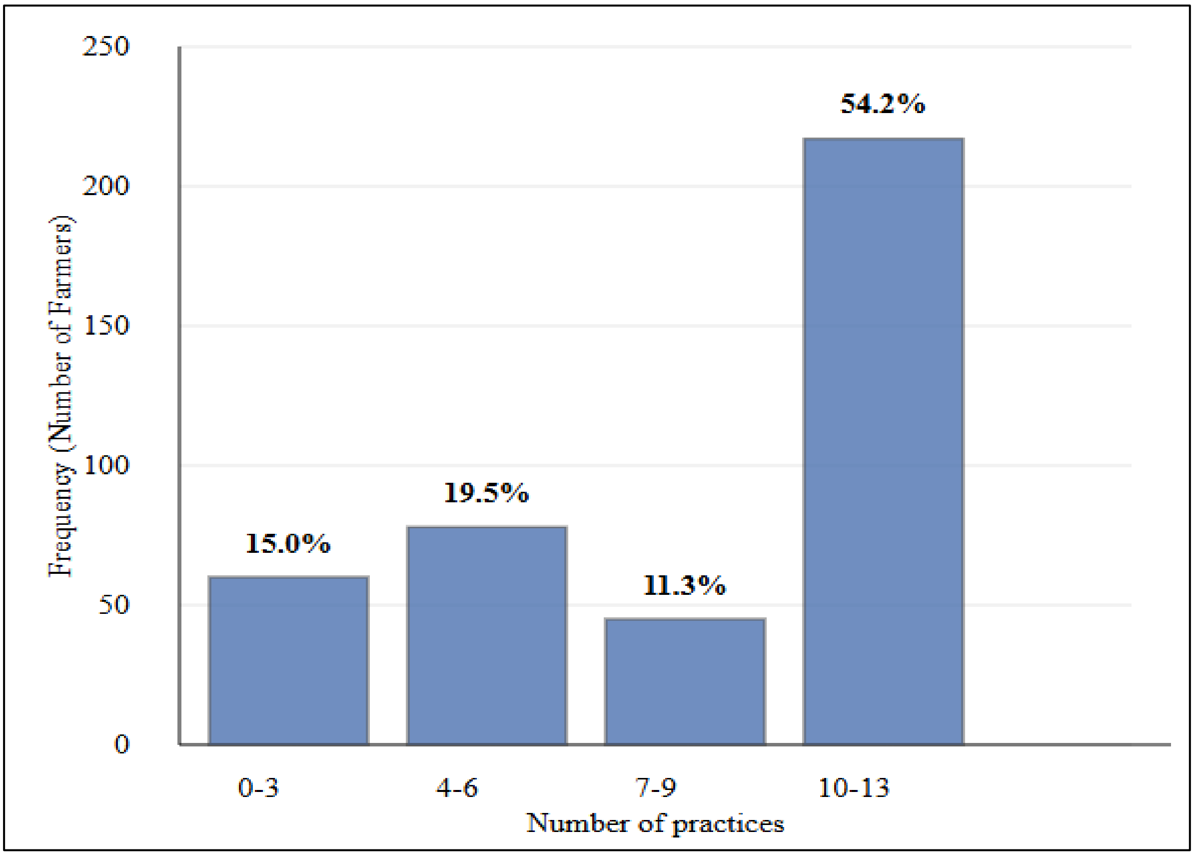

Figure 12: Bar graph distribution of farmers by level of awareness across the 13 CSA practices

3.3 Results related to how perception of CSA technologies influence adoption

Specific objective 2: *evaluate how perceptions of these technologies – framed through Rogers' innovation attributes – influence adoption*.

3.3.1 Factor analysis of Rogers' five perceived attributes

H2a tested whether farmers distinguish between Rogers five innovation attributes (relative advantage, compatibility, compatibility, observability) when evaluating CSA technologies.

A Principle Component Factor Analysis was conducted on the five-attribute item. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.872, and Bartlett's test of sphericity was significant ($\chi^2 = 8456.2$, df = 10, $p < 0.001$), confirming the data were suitable for factor analysis. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.872, indicating an excellent suitability for factor analysis, while Bartlett's Test of sphericity was significant ($\chi^2 = 8456.2$, $p < 0.001$), confirming that the variables were sufficiently correlated. One factor with an eigenvalue of 4.978 was extracted, explaining 99.8% of the total variance. All five attributes exhibited exceptionally high factor loading ranging from 0.997 to 0.998 and commonalities ranging from 0.994 to 0.996.

Result of the analysis extracted a single factor with an eigenvalue of 4.978, explaining 99.8% of total variance. All five attributes loaded strongly on this single factor (loading ranged from 0.997 to 0.998). No second factor had an eigenvalue greater than 1.

Table 10: Factor analysis of Rogers' innovation attributes

Attribute	Factor Loading	Communality
Relative advantage	0.998	0.996
Compatibility	0.997	0.994
Complexity (reversed)	0.998	0.996
Trialability	0.998	0.996
Observability	0.997	0.995
Eigenvalue	**4.978**	
KMO	**0.872**	
Bartlett's Test (χ^2)	**8456.2**	
Variance explained	**99.8%**	

Decision: we reject the null hypothesis that five attributes are distinguishable. Instead, they collapse into a single holistic dimension.

Interpretation: Exploratory factor analysis was conducted to assess the five innovation attributes (relative advantage, compatibility, complexity (reversed), trialability, and observability) derived from Rogers' Diffusion of innovation Theory and result showed that they represented a common underlying construct. These findings indicate that five innovative attributes collectively measure a single latent construct representing farmers' perceptions of climate-smart agriculture technology characteristics. In the context of climate-smart agriculture, farmers who perceive technologies as advantageous are also likely to perceive them as compatible with existing practices, easy to understand, observable and capable of being tested before full adoption. Thus, these attributes may be perceived holistically rather than independently, resulting in very high factor loading.

3.3.2 Relative importance of specific perception attributes

Hypothesis H2b tested whether perceived compatibility and trialability are the strongest predictors of adoption progression compared to relative advantage, complexity (reversed), and observability.

Multinomial logistic regression was used to examine how each perception attribute predicted membership in moderate vs, low adoption and high vs low adoption categories. Standardized beta coefficients (β) were compared to determine relative importance. Linear regression was also used for total progression score.

Results: for moderate adoption (vs low), compatibility had the largest coefficients (β =0.342, p < 0.003), followed by trialability (β = 0.215, p < 0.018). Relative advantage (β = 0.0189, p < 0.067) and ease of use (β = 0.156, p < 0.112) were not significant. For high adoption (vs low), trialability was the strongest predictor (β = 0.418, p < 0.001), followed by compatibility (β = 0.187, p < 0.032). Relative advantage was also significant but weaker (β = 0.223, p < 0.041). Observability was not significant in either model.

Table 11: Relative importance of perception attributes by adoption level

Perception Attribute	Moderate Adoption (β)	High Adoption (β)
Compatibility	0.342**	0.187*
Trialability	0.215*	0.418**
Relative advantage	0.189	0.223*
Ease of use (complexity reversed)	0.156	0.098
Observability	0.098	0.074

****p < 0.01, *p< 0.05**

Decision: we reject the null hypothesis. Compatibility and trialability are indeed the strongest predictors, though their relative importance shifts by adoption level.

Interpretation: The multinomial logistic regression results indicate that farmers' perceptions of innovation attributes significantly influence climate-smart agriculture adoption. These findings indicate that opportunities for experimentation, perceived benefits, and compatibility with existing practices are critical drivers of sustained adoption. In contrast, ease of use and observability were not significant predictors, suggesting that farmers place greater emphasis on practical benefits and experiential learning than on simplicity or visible outcomes when deciding to adopt climate-smart agricultural practices. Compatibility is most important during the early stages of adoption because farmers first evaluate whether a technology fits their existing farming systems. Trialability becomes increasingly important as adoption intensifies because farmers gain confidence through experimentation and direct experience. Relative advantage becomes significant among high adopters, suggesting that farmers continue adopting and investing in CSA practices when they perceive clear benefits. Ease of use and observability did not significantly influence adoption decisions in the study, although theoretically important in Rogers' framework.

3.3.3 Perception score by adoption level

H2c tested whether higher composite perception scores are associated with higher adoption levels.

A composite perception score (mean of five attributes, range 1-5) was calculated for each farmer. One-way ANOVA compared mean perception scores across low, moderate, and high adoption levels. Linear regression was then used to examine how perception score predicted total progression score (0-39).

Result of ANOVA revealed significant differences in perception scores across adoption levels ($F = 124.56$, $p < 0.001$). Low adopters had a mean perception score of 2.56 ($SD = 0.44$), moderate adopters scored 3.89 ($SD = 0.31$), and high adopters scored 4.98 ($SD = 0.12$). Linear regression showed that perception score explained 67% of the variance in adoption progression ($R^2 = 0.674$, $F = 823.45$, $p < 0.001$). Each one-point increase in perception score was associated with increase of 2.53 points in total progression score ($b = 5.23$, $SE = 0.18$, $\beta = 0.821$, $p < 0.001$)

Decision: we reject the null hypothesis. Higher perception scores are strongly associated with higher adoption levels

Interpretation: framers' overall positive perception of CSA technologies is a powerful driver of adoption. The near-linear relationship suggests that interventions aimed at improving perceptions (through demonstrations, success stories, and peer learning) can directly translate into higher adoption. The dramatic increase from low (2.56) to high (4.98) adopters indicates that perception is a critical advantage point.

Table 12: Perception score by adoption level

Adoption Level	Mean Perception Score (SD)	F-value	p-value
Low	2.56 (0.44)	124.56	< 0.001
Moderate	3.89 (0.31)	-	-
High	4.98 (0.12)	-	-

3.3.4 Perception as a predictor of adoption progression

H2c tested whether higher composite perception scores are associated with higher adoption levels.

A composite perception score (mean of five attributes, range 1-5) was calculated for each farmer. One way ANOVA compared mean perception scores across low, moderate, and high adoption levels. Linear regression was then used to examine how perception score predicted total progression score (0-39).

Result of ANOVA revealed significant differences in perception scores across adoption levels ($F = 124.56$, $p < 0.001$). Low adopters had a mean perception score of 2.56 ($SD = 0.44$), moderate adopters scored 3.89 ($SD = 0.31$), and high adopters scored 4.98 ($SD = 0.12$). Linear regression showed that perception score explained 67% of the variance in adoption progression ($R2 = 0.674$, $F = 823.45$, $p < 0.001$). Each one-point increase in perception score was associated with increase of 2.53 points in total progression score ($b = 5.23$, $SE = 0.18$, $\beta = 0.821$, $p < 0.001$)

Decision: we reject the null hypothesis. Higher perception scores are strongly associated with higher adoption levels

Interpretation: The results revealed significant differences in farmers' perceptions of climate-smart agriculture innovation attributes across adoption levels. These findings indicate that farmers with more favorable perception of climate-smart agriculture practices are more likely to belong to higher adoption categories. The significant ANOVA result confirms that perception attributes differ systematically across adoption groups, suggesting that positive perceptions of innovation characteristics play an important role in influencing adoption decisions.

Furthermore, the lower variability observed among high adopters indicates strong consensus regarding the benefits and sustainability of climate-smart agriculture practices among smallholder farmers who have extensively adopted these practices.

3.4 Results of how institutional factors and livelihood assets shape CSA adoption

Specific Objective 3: *Examine how institutional factors (policies, markets, cooperatives) and livelihood assets (human and social capital) shape CSA adoption*

3.4.1 Descriptive statistics of institutional factors

Table 13: Frequency of institutional factors and social indicators

Variable	Category	n	%
Extension contact (past year)	At least one contact	187	46.8
	No contact	213	53.2
Cooperative membership	Member	156	39.0
	Non-member	244	61.0
Credit access	Yes	98	24.5
	No	302	75.5
Market access	Good/Very good	134	33.5
	Poor/Very poor	266	66.5
Advice-sharing with other farmers	Frequently	289	72.3
	Rarely/Never	111	27.7

Interpretation: The results indicate that farmers generally have limited access to institutional and financial support services. More than half of the respondents (53.2%) had no extension contact during the previous year, 61.0% were not members of the cooperatives, 75.5% lacked access to credit, and 66.5% reported poor or very poor market access. These findings suggest constraints in access to information, financial resources, and market opportunities that may hinder the adoption of climate-smart agriculture practices. However, substantial proportion of farmers (72.3%) frequently share farming advice with fellow farmers, highlighting the importance of informal social networks as a source of agricultural knowledge and innovation diffusion. Overall, the findings suggest that while institutional and financial capital remain limited, strong social capital in the form of farmer-to-farmer interactions may help facilitate the dissemination and uptake of climate-smart agriculture practices.

3.4.2 Multinomial logistic regression: Determinants of adoption levels

Hypothesis H3c tested whether age is strongly associated with adoption while farming experience shows a positive but weaker association

Multiple linear regression (entered method) was used with total awareness, total knowledge, and total principles as dependent variables. Age (continuous) and farming experience (continuous) were entered as predictors along with gender, education, and income. Multinomial logistic regression also examined age, and experience as predictors of adoption levels

Results in Table 14 show that the multinomial logistic regression overall model was significant ($\chi^2 = 66.819$, df = 46, $p < 0.024$). For moderate adoption vs. low adoption: age (OR = 0.610, $p < 0.004$) and gender (OR = 0.092, $p < 0.021$) were significant, with age decreasing the odds and male gender (relative to female) decreasing the odds of being a moderate adopter. For high adoption vs. low adoption: age (OR = 0.391, $p < 0.001$), farming experience (OR = 1.322, $p < 0.013$), gender (OR = 0.068, $p < 0.019$), and cooperative membership (OR = 1.693×10^{-13}, $p < 0.026$) were significant**.** Extension services approached but did not reach significance (OR = 0.088, $p < 0.055$).

Table 14: Multinomial logistics for adoption level

Variable	**Moderate vs. Low**		**High vs. Low**	
	B (SE)	**Odds Ratio**	**B (SE)**	**Odds Ratio**
Age	-0.494 (0.171)**	0.610	-0.939 (0.227)***	**0.391**
Farming Experience	0.108 (0.089)	1.114	0.279 (0.112)*	**1.322**
Gender (Male)	-2.386 (1.033)*	0.092	-2.694 (1.144)*	**0.068**
Extension services (No)	-1.915 (1.147)	0.147	-2.427 (1.266)	**0.055**
Cooperative Membership (No)	-16.863 (1111.988)	4.75E-8	-29.407 (1732.396)*	**1.69E-13**

*Note: *p< 0.05, **p < 0.01, ***p < 0.001. Reference category is Low Adoption.*

Decision: We reject the null hypothesis. Age, gender, farming experience, and cooperative membership are significant predictors.

Interpretation: Moderate adoption vs Low adoption: For multinomial logistic regression, the B coefficient represents the change in the log-odds of being in a higher adoption category relative to the reference category. The multinomial logistic regression further showed that for every one-unit increase in age (B = -0.494; OR = 0.610), the odds of being a moderate adopter rather than a low adopter decrease by 39.0%. Gender (Male) (B = -2.386; OR = 0.092) have 90.8% lower odds of being moderate adopters compared with female farmers. **High adoption vs Low adoption** age (B = -0.939; OR = 0.391) suggests that each additional year of age decreases the odds of being a higher adopter by 60.9%. Farming experience (B = 0.279; OR = 1.322) indicates that each additional year of farming experience increases the odds of being a high adopter by 32.2%. Gender (Male) (B = -2.694; OR = 0.069) suggests that male farmers have 93.2% lower odds of being a high adopter than female farmers. Cooperative membership (No) (B = -29.407; OR = 1.69×10^{-13}**)** suggests that farmers who were not cooperative members had virtually zero odds of being high adopters compared to cooperative members. This suggests a very strong association between cooperative membership and high adoption levels. Conclusively, younger age, greater farming experience, female gender, and cooperative membership significantly increase the odds of being in a higher adoption category. These findings partially support hypothesis H3c, indicating that age is the strongest determinant of adoption-related outcomes, while farming experience exerts a positive but comparatively weaker effect. The extremely low odds ratio for cooperative membership (1.693×10^{-13}) reflects the fact that all cooperative members are concentrated in the high adoption category (74.4% of members are high adopters, as shown in Table 14). The near-significant effect of extension contact ($p < 0.055$) suggests a positive trend that may become significant with a larger sample or improved extension quality.

3.4.3 Linear regression: Factors associated with awareness, knowledge, and principles

Hypothesis H3c: the combination of demographic factors (age, gender, education, farming experience and annual income)

Three separate multiple linear regression models (enter method) were estimated, each using the same independent variable (age, gender, education, farming experience and annual income). Dependent variables were total awareness, total knowledge, and total principles for each model R2, adjusted R2 and F-test statistics were computed to assess overall model fit and significance.

Result **Model for total awareness** explained 83.1% of the variance ($R^2 = 0.831$). Age ($\beta = -0.743$, $p < 0.001$), gender ($\beta = 0.063$, $p < 0.007$), education ($\beta = 0.299$, $p < 0.001$), and farming experience ($\beta = 0.151$, $p < 0.002$) were significant predictors (Table 13). **Model for total**

knowledge explained 87.2% of variance ($R^2 = 0.87$). Age ($\beta = -0.682$, $p < 0.001$), education ($\beta = 0.372$, $p < 0.001$), farming experience ($\beta = 0.121$, $p < 0.005$), and income ($\beta = 0.037$, $p < 0.045$) were significant predictors (Table 4.14). **Model for total principles** explained only 7.6% of variance ($R^2 = 0.076$). Age ($\beta = -0.396$, $p < 0.007$), farming experience ($\beta = 0.277$, $p < 0.017$), and income ($\beta = 0.183$, p ¸0.001) were significant predictors while gender and education were not (Table 15)

Table 15: Linear regression for total awareness

Variable	B	Std. Error	Beta	t	p-value
(Constant)	19.590	1.412		13.874	**<0.001**
Age	-0.345	0.029	-0.743	-11.938	**<0.001**
Gender	0.540	0.197	0.063	2.734	**0.007**
Education Level	1.359	0.206	0.299	6.600	**<0.001**
Farming Experience	0.059	0.019	0.151	3.047	**0.002**
Annual Income	1.753E-6	0.000	0.029	1.360	**0.175**

*$R^2 = 0.831$, Adjusted $R^2 = 0.829$, $F = 388.322$, $p < 0.001$

Table 16: Linear regression for total knowledge

Variable	B	Std. Error	Beta	t	p-value
(Constant)	18.933	1.393		13.589	**<0.001**
Age	-0.358	0.028	-0.682	-12.567	**<0.001**
Gender	0.361	0.195	0.038	1.854	**0.064**
Education Level	1.912	0.203	0.372	9.410	**<0.001**

Farming Experience	0.054	0.019	0.121	2.808	**0.005**
Annual Income	2.561E-6	0.000	0.037	2.014	**0.045**

$R^2 = 0.872$, Adjusted $R^2 = 0.870$, $F = 535.578$, $p < 0.001$

Table 17: Linear regression for total principles

Variable	B	Std. Error	Beta	t	p-value
(Constant)	11.888	2.062		5.765	**<0.001**
Age	-0.115	0.042	-0.396	-2.715	**0.007**
Gender	0.237	0.288	0.045	0.821	**0.412**
Education Level	-0.089	0.301	-0.031	-0.296	**0.767**
Farming Experience	0.068	0.028	0.277	2.391	**0.017**
Annual Income	-6.965E-6	0.000	-0.183	-3.702	**<0.001**

$R^2 = 0.076$, Adjusted $R^2 = 0.064$, $F = 6.463$, $p < 0.001$

Decision: we reject the null hypothesis for each model (all f-tests significant). The demographic factors collectively explain a large and significant portion of variance in awareness and knowledge, but a very small portion in principles,

Interpretation: The standardized beta coefficients revealed that age was the most influential predictor across all three models, exhibiting a strong negative effect on awareness ($\beta = -0.743$), knowledge ($\beta = -0.682$), and principles ($\beta = -0.396$). This indicates that younger farmers generally possessed higher awareness, knowledge, and understanding of climate-smart agriculture than older farmers. Education was the second most important predictor of awareness ($\beta = 0.299$), and knowledge ($\beta = 0.372$), and understanding principles ($\beta = -0.031$) suggesting that formal education enhances farmers' capacity to acquire and understand climate-smart agriculture information. Farming experience demonstrated a positive but weaker influence across the first two models: awareness ($\beta = 0.121$), and knowledge ($\beta = 0.121$), but stronger for understanding of principles ($\beta = 0.277$). This indicates that farers with more years of farming experience tend to possess better understanding and application of principles of climate-smart agriculture practices, supporting the hypothesis that experience contributes to awareness, knowledge and understanding of climate-smart agriculture. Annual income was not significant predictor of awareness ($\beta = 0.029$, $p = 0.175$) after controlling for other variables. Concerning knowledge, annual income had a statistically significant but weak positive effect ($\beta = 0.037$, $p = 0.045$), indicating that farmers with higher incomes tend to have slightly higher knowledge levels. For understanding principles, annual income had a significant negative effect ($\beta = 0.183$, $p<0.001$) suggesting that farmers with higher incomes tend to have lower principle scores after controlling for other factors. The acceptable VIF values confirm that multicollinearity did not affect the reliability of the estimated coefficients. These findings support the hypothesis that demographic characteristics significantly influence farmers' awareness, knowledge and understanding of climate-smart agriculture, with age exerting the strongest effect and farming experience showing a positive but comparatively weaker influence.

Model performance: the awareness model explained 83.1% of the variance in awareness scores ($R^2 = 0.831$, p ¸0.001), indicating an excellent explanatory power. Similarly, the knowledge model explained 87.2% of the variance in knowledge score ($R^2 = 0.872$, $p < 0.001$), demonstrating a very strong model fit. In contrast, the principles model explained only 7.6% of variance ($R^2 = 0.076$, $p < 0.001$), suggesting that factors not included in the model may play a more important role in shaping farmers' understanding and application of climate-smart agriculture principles

3.4.4. The role of cooperative membership

Hypothesis H3a tested whether cooperative membership significantly increases the odds of being in higher adoption categories (moderate or high) compared to non-members.

Multinomial logistic regression was conducted with adoption level (low = reference category) as the dependent variable and cooperative membership (dummy: 0 = non-member, 1 = member) as an independent variable, controlling for age, farming experience, gender, and extension contact. Odds ratios (OR) with 95% confidence intervals were calculated. A chi-square test of independence was also performed on the cross-tabulation of cooperative membership by adoption level.

Result shows that cooperative membership was significant predictor of high adoption vs low adoption ($B = -293407$, $SE = 1732.396$, $OR = 1.69 \times 10^{-13}$, $p < 0.026$). For moderate vs low adoption, the coefficient was also large but not significant (B = -16.863, $p < 0.988$). The cross tabulation (Table 4.16) showed that 74.4% of cooperative members were high adopters, compared to only 27.0% of non-members ($\chi^2 = 89.34$, $p < 0.001$)

Table 18: Adoption level by cooperative membership (Cross-tabulation)

Cooperative Member	Low Adoption	Moderate Adoption	High Adoption	Total
Yes	12 (7.7%)	28 (17.9%)	116 (74.4%)	156
No	126 (51.6%)	52 (21.3%)	66 (27.0%)	244
$\chi^2 = 89.34$, $p < 0.001$				

Decision: We reject the null hypothesis. Cooperative membership significantly increases the odds of being a higher adopter.

Interpretation: The Chi-square analysis revealed a statistically significant association between cooperative membership and CSA adoption levels ($\chi^2 = 89.34$, $p < 0.001$). Among cooperative members, 74.4% were high adopters, compared to only 27.0% of non-adopters. Conversely, over half of non-members (51.6%) were low adopters, whereas only 7.7% of cooperative members fell into the low adoption category. These findings suggest that cooperative membership substantially increases farmers' likelihood of adopting CSA practices. Cooperatives serve as important social networks through which farmers access information, training, credit facilities, agricultural inputs, market opportunities, and peer learning. Membership also facilitates collective action and knowledge sharing, thereby reducing barriers to technology adoption. The multinomial logistic regression further confirmed the importance of cooperative membership, showing that non-members had significantly lower odds of belonging to the high-adoption category

3.4.5 The role of extension services

Hypothesis H3b tested whether contact frequency is positively associated with awareness, knowledge, and adoption levels.

Extension contact was measured as a dummy variable (0 = no contact in past year, 1 = at least one contact). Linear regression models for total awareness and total knowledge originally included demographic variables only; extension contact was added in a separate model for this hypothesis. Multinomial logistic regression included extension contact as a predictor of adoption level.

Result in Table 4.11 shows that in the multinomial regression for high vs low adoption, extension contact (coded as “No”) had a coefficient of B = -2.427 (SE = 1.1266, $p < 0.055$). The odds ratio was 0.088, but the p-value just exceeded the coefficient for awareness was positive but not significant ($\beta = 0.042$, $p < 0.183$). Descriptive analysis showed that among farmers with extension contact, 61.5% were high adopters, compared to 48.4% among those without contact. Extension contact approached but did not reach statistical significance in the multinomial regression ($p = 0.055$ for high vs low adoption). Descriptive analysis showed that among farmers with extension contact, 61.5% were high adopters, compared to 48.4% among those without contact.

Decision: we fail to reject the null hypothesis. There is sufficient evidence at the $p < 0.05$ level to conclude that extension contact is positively associated with adoption. However, the trend ($p < 0.055$) approaches significance.

Interpretation: Although extension services were not statistically significant at the 5% level in the multinomial logistic regression (OR = 0.088, $p = 0.055$), the variable was very close to significance. This suggests that extension contact may still play an important role in influencing adoption behavior. Extension services contribute to farmers’ human capital by improving technical knowledge, awareness of climate risks and understanding of CSA practices. Farmers who receive extension support are more likely to access information on improved farming practices, climate adaptation strategies, and technology utilization. The near-significant result indicates that extension services may positively influence adoption, but their effect may be constrained by factors such as limited coverage, irregular visits, inadequate staffing, or variability in the quality of advisory services. Therefore, while extension services alone may not fully explain adoption differences in this sample; they appear to be an important enabling factor that complements other assets such as education, experience, and cooperative membership.

3.4.6 Age and farming experience as human assets

Hypothesis H3c tested whether age is strongly associated with adoption while farming experience shows a positive but weaker association

Multiple linear regression (entered method) was used with total awareness, total knowledge, and total principles as dependent variables. Age (continuous) and farming experience (continuous) were entered as predictors along with gender, education, and income. Multinomial logistic regression also examined age, and experience as predictors of adoption levels

Results in linear regression for total awareness shows that age was the strongest negative predictor ($\beta = -0.743$, $p < 0.001$), while farming experience showed a positive but weaker effect ($\beta = 0.151$, $p < 0.002$). For total knowledge, age ($\beta = -0.682$, $p < 0.001$) and experience ($\beta = 0.121$, $p < 0.005$) followed the same pattern. For total principles, age ($\beta = -0.396$, $p < 0.007$) and experience ($\beta = 0.277$, $p < 0.017$) again showed negative and positive effects respectively, with experience having a relatively larger coefficient for principles. In multinomial logistic regression, age significantly decreased the odds of being a moderate adopter (OR = 0.610, $p < 0.004$) and a high adopter (OR = 0.391, $p < 0.001$). Farming experience increased the odds of high adoption (OR = 1.322, $p < 0.013$).

Decision: we reject the null hypothesis. Age is negatively associated with adoption and farming experience is positively associated, though the effect of experience is weaker for awareness and knowledge but strong for principles.

Interpretation: the finding indicates that age and farming experience, as key components of human capital, play important but contrasting roles in influencing climate-smart agriculture adoption. Age exhibited a strong negative association with awareness, knowledge, principles and adoption levels, suggesting that younger farmers are more likely to acquire information, embrace innovation, and adopt CSA practices. This may be attributed to their greater openness to change, higher willingness to take risks, and increased exposure to modern information and communication technologies. In contrast, farming experience showed a positive association with awareness, knowledge, principles and high adoption levels, indicating that accumulated practical knowledge and skills gained through years of farming enhance farmers' ability to recognize climate risks and appreciate the benefits of adaptation strategies. The positive influence of farming experience suggests that experiential learning strengthens farmers' adaptive capacity and supports informed decision-making regarding technology adoption. Taken together, these results demonstrate that human capital is multidimensional, with younger age fostering innovation receptiveness while farming experience contributes valuable practical expertise. Consequently, younger farmers with substantial farming experience may possess the greatest capacity to adopt and effectively implement climate-smart agricultural practices.

3.4.7 Model fit summary for objective 3

The combination of demographic, institutional, and perceptual factors explained 83.1% of variance in awareness and 87.2% in knowledge, but only 7.6% in understanding of principles. This indicates that extension and institutional support systems are effective at building procedural knowledge but fail at developing conceptual understanding.

CHAPTER V: PUBLICATION MANUSCRIPT II

Mediated Influence of Digital Agriculture Technologies on Climate-Smart Agriculture Decisions among Smallholder Farmers in Sub-Saharan Africa: A Systematic Review

ABSTRACT

Digital agricultural technologies like remote sensing, geographic information systems (GIS) Artificial intelligence (AI), mobile-based advisory services, and internet of things (IoT) potentially promise to enhance smallholder farmers' climate-smart agriculture (CSA) adoption decisions in sub-Saharan Africa (SSA). This study examine how digital technologies influence smallholder farmers' decision-making in relation to climate-smart practices adoption decision among smallholder farmers in SSA with focus on identifying key technological pathways that enhance adaptive capacity and resilience to climate change. The study examined the role of digital agricultural tools in influencing CSA adoption A critically analysis of 82 selected peer-reviewed articles published between 2015 and 2025 identified through academic databases including Scopus, Web of Science, and Google Scholar. The review synthesized findings to identify consistent pathways through which digital tools support climate adaptation and agricultural resilience. Results indicate that digital technologies influence decision-making through three pathways: real-time information provision using IoT sensors and remote sensing, predictive analytics for climate-risk assessment using artificial intelligence, and machine learning, and optimized timing of farm operations through digital advisory and early warning systems. Empirical evidence show improvements in resource use efficiency, yield stability, and climate-risk preparedness using decision-support tools although adoption remains constrained by barriers such as limited digital literacy, infrastructural challenges, affordability constraints institutional capacity, social fabric limitations, and gender inequality. We conclude that digital technologies significantly enhance CSA adoption, by reducing uncertainty and improving farm-level decision-making, although investment in infrastructure, digital literacy and institutional support remains critical for scaling sustainable climate adaptation outcomes.

Keywords: Digital agriculture, smallholder farmers, decision-making, climate-smart agriculture, sub-Saharan Africa

INTRODUCTION

1.1 Climate change and smallholder agriculture in sub-Saharan Africa

Climate change substantially jeopardizes food systems all over the world and sub-Saharan Africa (SSA) endures the most of the effects of climate variability despite minimal contribution to greenhouse gas emissions. The region is home to about 77 million smallholder farmers Lowder et al. (2016), constituting 80% of the total farmers' population (IFAD, 2014). Surprisingly, less than 5% of Sub-Saharan Africa's arable land is supported by irrigation infrastructure Wiggins & Lankford (2019); You et al. (2011). This means that agricultural production is overwhelmingly rain-fed, with reports indicating that 95% of smallholder farmers rely on natural rain for their farming activities Abrams (2018) and Dadzie et al. (2024)– hindering their productivity and resulting in food insecurity.

Most of the farmers typically operate less than two hectares of land and are the most vulnerable to climatic risks yet constitute the backbone of food security in the region (Lowder et al., 2016; Ricciardi et al., 2018). Climate shocks like elevated temperatures, continuous erratic precipitation and frequent weather events threaten the region's agricultural productivity (Manono et al., 2025; Mutengwa et al., 2023). Over the decades, farming has revolutionised from rudimentary to a more technology-oriented production. For instance, the emergence of climate-smart agriculture (CSA) that integrates approaches to transform agricultural systems through leveraging available knowledge and innovation to reduce emissions, enhance productivity, foster resilience and elevate food security (Kabato et al., 2025; Ariom et al., 2022). Such approaches include conservation agriculture, agroforestry, improved water management, drought resilient cop varieties and integrated soil fertility management among other practices (Ariom et al., 2022; Oyelemi et al., 2023).

1.2 The digital agriculture promise

Beyond the development of climate-smart agriculture, advancements in digital technology have opened new frontiers for agricultural decision-making (Mollel et al., 2025; McFadden et al., 2022). These advancements hold transformational potential for smallholder farmers, by facilitating resource optimization through data-driven decisions (Mhlanga & Ndlovu, 2023). As Basso & Antle (2020) argue, digital agriculture offers pathways to designing sustainable agricultural systems through precision technologies that optimize resource use while maintaining productivity. Incorporating digital technologies in farming systems has a direct bearing in assisting farmers to leap from reliance on traditional farming practices to embracing precision farming for sustainability, enhanced productivity and resilience (Alsanhani et al., 2025; Assimakopoulos et al., 2024; Abdulai et al., 2023).

Technologies such as remote sensing incorporating satellite imageries and drone-based sensors foster monitoring crop vigor, soil conditions and availability of water at spatial and temporal scale Onyango et al. (2021) and Nyaga et al., (2021), thereby, helping farmers in making informed decisions on the most appropriate action to be taken. Geographic information systems (GIS)-based tools like ArcGIS or QGIS software enables spatial analysis of farming terrains, and enables resource optimization and site-specific management recommendations (Fetene, 2021). Internet of things technologies such as soil sensors, weather stations and automated irrigation systems offer real-time data on conditions of the field, allowing farmer a responsive management decisions (Ayaz et al., 2019; Tzounis et al., 2017; Bacco et al., 2019; Rajack et al., 2023; Gatkal & Sharma, 2024).

Conclusively, these technologies support decision-making in three practical ways. For instance, availing real-time data on soil moisture content, crop vigor that inform targeted fertiliser application (Kuradusenge et al., 2024; Bayih et al., 2022). Similarly, smart irrigation Nigussie et al. (2020) initiate early warning for climate risks such as floods and pest invasions Mmbando (2025); Foster et al. (2023) supporting climate modeling that enables long term planning Bashiru et al. (2024) as well as linking farmers to a weather-index insurance and carbon markets (Shaibu et al., 2025).

1.3 Digital agriculture in sub-Sahara African context

Sub-Saharan Africa possesses prospect for digital agriculture among her farming population, however, the region faced unique drawbacks for digital agriculture technology adoption, a contribution of several factors spanning infrastructural limitation, economic constraints , social and cultural considerations and institutional rigidity (Chepkemoi et al., 2025; Chisanga et al., 2025; Tsan et al., 2019; Mhlanga & Ndhlovu. 2023). Despite the region high potential and greater number of smallholder farmers, challenges like poor internet coverage, and digital low literacy limits accessibility to technologies (Cariolle, 2021; Jellason et al., 2021; GSMA, 2021; Bonsta et al., 2023).

Economically, the region lags behind in digital agriculture adoption, as most of the farmers are resource poor, faces expensive digital tools, and limited in accessing credit facilities resulting to challenges of affordability (Onyango et al., 2021; Addison, 2024). The region has a fair share of societal induced challenges including social constructs like gender differentiation, consumption of local knowledge and limited digital knowledge undermines technology acceptance (Khoza et al., 2021; Thothela et al., 2021; BSMA, 2022; Leta et al., 2023); (Thothela et al., 2021). Besides, frail extension services devoid of technical support and disjointed policies hinder technology promotion and sustainability in the sub-Sahara Africa (Ayim et al., 2022; Habiyaremi et al., 2024).

1.4 Research gap and unique contribution of the study

Despite rapid development, sustained promotion, and interest in digital agriculture, significant gaps remain in understanding how remote sensing, GIS, and IoT technologies practically influence CSA adoption decisions of smallholder in SSA (Jellason et al., 2022; Nyaga et al., 2021).

This review identifies three critical gaps that justify the need for the present study:

Lack of integrated influence mechanisms. Existing research tends to examine individual technologies in isolation, failing to synthesize how different digital tools collectively shape decision-making processes (Choruma et al. 2024; Nyagaet et al., 2021). Choruma et al. (2024) note in their scoping review of digitalisation in African agriculture that there is limited integration across technology types in understanding farmer decision-making outcomes. Similarly, Onyango et al. (2021) observed that precision agriculture studies in SSA typically focus on single technologies without examining how combinations of tools interact to influence farmer behaviour. Klerkx & Rose (2020); Geels, (2022) and Ayim et al. (2022) further emphasize that technology adoption studies often treat tools as discrete interventions rather than integrated systems. Few studies comprehensive framework that currently explains the pathways through which remote sensing, GIS and IoT technologies translate data into farmer action.

Limited attention to contextual determinants. While adoption constraints are frequently mentioned, the interconnectedness nature of infrastructure, economic, institutional, and gender barriers remain undertheorized (Mlhanga & Ndhlovu, 2023; Botsa et al. 2023). Khoza et al. (2021) emphasize that gender barriers intersect with other constraints to enhance systemic exclusion, yet integrated analysis remain rare. Zougmoré & Partey (2022), GSMA (2022) and Appiah et al. (2025) further document that gender disparities compound other barriers to technology adoption. Bashiru et al. (2024) similarly note that most adoption studies treat barriers as independent rather than interconnected, limiting understanding of why technologies succeed in some contexts but fail in others. It is therefore essential to understand how these factors interact to create systematic exclusion for designing effective interventions.

Absence of scalability analysis. The literature predominantly features pilot studies with limited attention to what enables or constrains scaling (Kreft et al. 2023). The persistent “pilot-to-scale” gap where successful demonstration fail to achieve widespread adoption requires systematic investigation. Jellason et al. (2021) highlight that “most digital agriculture interventions in SSA remain at pilot scale, with limited evidence on what dives successful scaling.” Rurii & Nzengya (2026) further emphasize that “without understanding scaling mechanisms, technology adoption remains episodic rather than transformative.” Choruma et al. (2024) and Appiah et al. (2025) document that fewer than 10% of digital agriculture initiatives reach scale beyond pilot projects.

This review offers a novel integrated socio-technical framework that bridges the gaps between technical potential and practical reality, drawing on socio-technical literature Geels, (2019) and adaptation pathways approaches (Sietz et al., 2022). Unlike existing reviews that focus solely on climate impact or digital tools in isolation, we (i) synthesise evidence across four technology types (remote sensing, GIS, IoT, and ML) to identify common influence pathways while systematically analyzing the interconnected barriers that shape adoption outcomes. (ii) We integrate evidences across four technology types using unified framework, and (iii) map the interconnections between infrastructural, economic, institutional, and gender barriers; analyzed the pilot-to-scale gaps as design problem requiring systematic solutions. Our framework explicitly connects climate resilience with the socio-economic and structural factors such as digital divide, gender inequality, and policy gaps that determine whether the technology reach and benefit the most vulnerable farmers (McFodden et al., 2022). This integrated perspective provides researchers, practitioners, and policymakers with a holistic understanding of both the promise and the present challenges of digital agriculture in SSA. The main aim extends beyond documenting negative climate impacts to examining how digital technologies function as both impacted by and solution to climate challenges, consistent with the dual farming advanced by (Zougmoré et al., 2021; Partey et al., 2020).

2. MATERIALS AND METHODOLOGY

2.1 Protocol and registration

The review followed a detailed guideline of Proffered Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol Page et al. (2021) to ensure transparency and reproducibility. The review outlines clear steps for a systematic identification, selection and synthesis of relevant information from the past publications. Due to the nature of the review, no protocol was registered in PROSPERO.

2.2 Scope of the study

Implementation of digital agriculture technology: the study focuses on the practical application and use of digital technologies particularly remote sensing, geographic information system and internet of things in a smallholder farmers set-up confined to actual in-field settings and in an on-farm study site within sub-Saharan Africa.

Influence on decision-making: the precise aim of the study lies in understanding how application of these digital technologies inform decision-making processes of smallholder farmers' to adopt climate-smart agriculture practices. The study is limited to evidences indicating smallholder farmers actively engaged with these technologies as opposed to scenarios where farmers are side lined or reduced to being observers.

Methodology: this study focuses on primary research demonstrating methodological rigor including qualitative, quantitative or mixed method and systematic reviews as well as meta-analyses where empirical data is synthesised. Any study that theorise the use of these technologies and without farmer focus were excluded.

2.3 Search strategy

The study conducted a detailed search spanning multiple databases including Google Scholar, and Web of Science. Following search strategies recommended by Lefebvre et al. (2019) for systematic reviews. A combination of key words including "remote sensing," "GIS," "geographic information system," "IoT," "internet of things," "climate-smart agriculture," "CSA," "smallholder farmers," "small-scale farmers," "decision-making," "adoption," and "sub-Saharan Africa" informed the search strategy. The research focused on papers published only between 2017 and 2025 in English language to capture the most recent evidence. The review further applied Boolean Operators to search for articles titles with the following specific search strings: ("remote sensing" OR "GIS" OR "geographic information system OR "IoT" OR "internet of things") AND ("Climate-smart Agriculture" OR "CSA") AND ("smallholder farmer" OR "small-scale farmer") AND ("Decision-Making" OR "Adoption") AND ("sub-Saharan Africa" OR "Africa"). The combination of terms using Boolean Operators aimed at maximizing search sensitivity form the databases

2.4 Eligibility criteria

The study type in this review included only peer-reviewed articles in the journals, Doctoral theses, institutional reports, grey literature and conference proceedings published between 2017 and 2025.

2.4.1 Inclusion criteria

The study considered the materials intended for analysis based on the following tenets:

Population: Studies solely focusing on smallholder farmers in sub-Saharan Africa potentially predisposed to climate risks.

Technology intervention: Studies examining remote sensing, GIS-based tools and IoT technologies application in agricultural settings.

Decision-making outcomes: Studies reporting mechanisms of how technologies influence decision-making process for adopting climate-smart agriculture.

Study type: Empirical research employing qualitative, quantitative, mixed-methods, case studies, systematic reviews, informed the inclusion criteria, rather than opinion pieces or purely theoretical papers,

Publication quality: Studies published in peer-reviewed academic journals, conference proceedings, and credible institutional reports.

Publication period: Studies published in English between 2017 and 2025

2.4.2 Exclusion criteria

Studies were excluded if they:

Were published before 2017
Lacked methodologies or presented general conclusions
Focused on technology types other than GIS, IoT and remote sensing
Lacked publication dates, authors and in other languages
Did not focus on smallholder farmers and confined outside sub-Saharan Africa.

2.5 Screening process

An initial search generated from four databases (Scopus, Web of Science, Science Direct, and Google Scholar) yielded 9,246 potential studies, which were subjected to data cleaning by removing duplicates (3,918). This resulted to 5,328, records which were screened by title and abstract. Upon the screening, 4,892 records were excluded for various reasons allowing a full text review of 436. The full text review generated 76 records. The review also retrieved 10 records generated from other sources, assessed their eligibility in which 4 records were excluded while 6 passed eligibility tests. In the end of screening, 82 studies were ultimately included for synthesis.

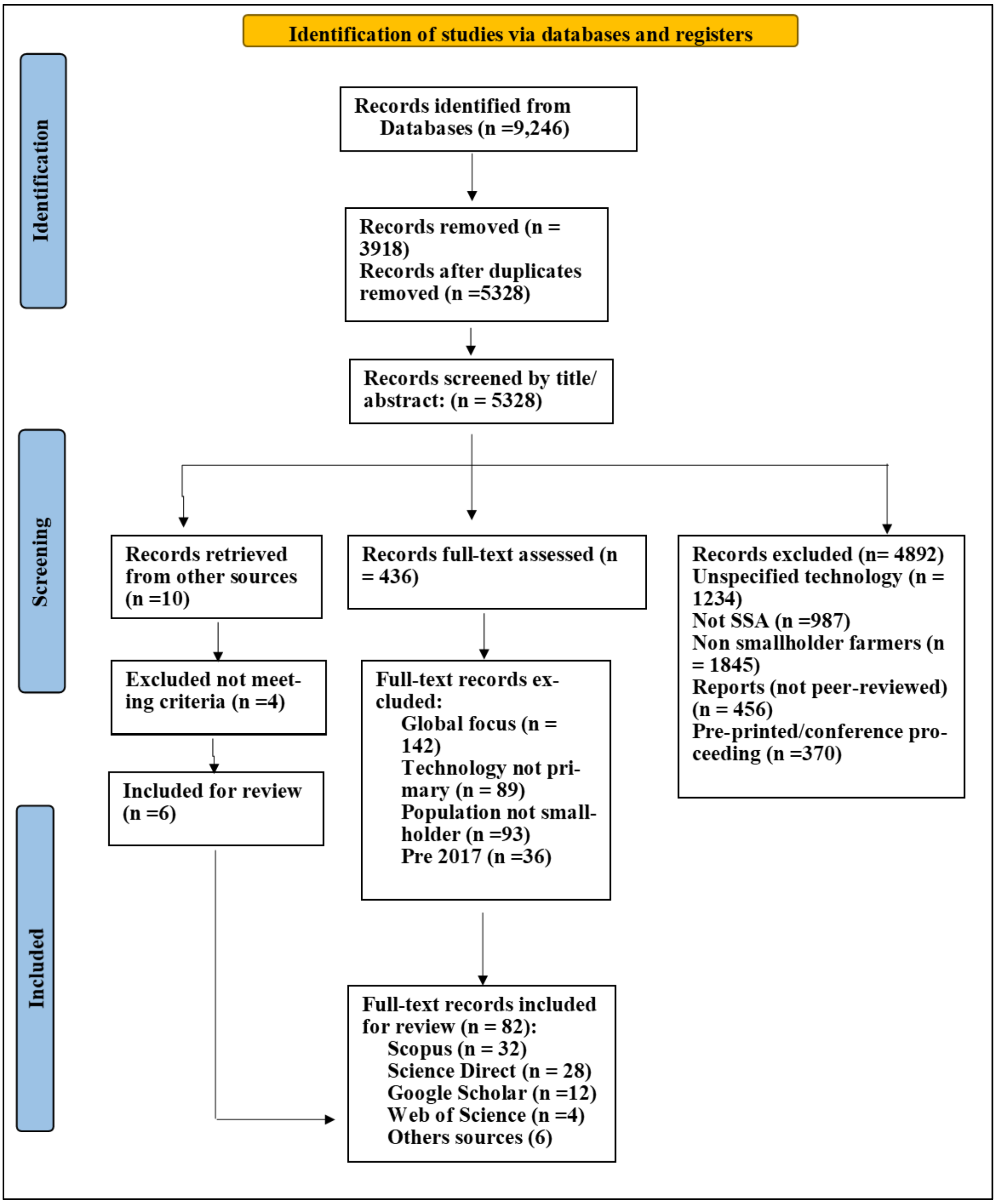

Figure 1: PRISMA flow diagram for screening process

2.6 Data extraction mechanism

Data extraction employed a standardised framework developed to capture:

Study characteristics: Author, year, geographic niche, methodology and key findings

Technology focus: Type of remote sensing, GIS and IoT technology examined

Decision-making influence: Mechanism and evidence of influence on farmer decisions.

CSA practices examined: specific practices and reported adoption rates.

Adoption determinant: Enablers and barriers characterized by factor type.

Integration approaches: how technologies were deployed and with what support systems
Contextual factors, socio-economic, infrastructural, and institutional conditions

The study used Scispace AI data extraction tool to ensure accuracy, with all the extracted data verified manually by the authors.

2.7 Data synthesis

Thematic synthesis of data included organizing the data into key domains identified in the research question. Given heterogeneity in the study designs, technology types, and outcome measures, the review conducted narrative synthesis following Petticrew & Roberts (2008) guidance for narrative synthesis in systematic reviews and recommendations for complex policy relevant reviews. Thematic analysis organized data into key domains identified in the research questions, with patterns and relationships identified across studies.

3. RESULTS

3.1 Characteristics of included studies

The review included 67 sources published between 2017 and 2026. Geographically, the studies covered 15 (multi-country) analyses and (15) individual sub-Saharan Africa countries, with South Africa (9), Kenya (8), Ethiopia (7) and Ghana (6) being mostly represented. In terms of regional representation, East Africa registered the highest number of studies (21), followed by Southern Africa (18) and Western Africa (14). Central Africa is notably absent from the single-country studies. The multi-country studies (16) takes a regional or continental perspective, providing valuable cross-country comparison and synthesis. The review synthesises the included studies by geographic focus outlining the country or region, number of studies done in specific country or multiple countries, methodology applied in the study, and representative authors as shown in table 1.

Table 1: Summary of included studies by region

Country/region	Number of studies	Methodology used	Representative author
Ghana	6	Quantitative surveys, mixed-methods	Shaibu et al. (2025); Bismark et al. (2021); Asante et al. 2024); Moomen et al. (2024);

Kenya	8	Systematic review, book chapter, review	Mmbando (2025); Manzi & Gweyi-Onyango (2021); Muthoni (2023); Wahome et al. (2023); Chepkemoi et al. (2025); Njuguna et al. (2025)
Nigeria	3	Quantitative survey, experimental design	Bashiru et al. (2024) Okoh et al. (2023); (Adenubi et al. (2021)
South Africa	9	Geospatial analysis, quantitative survey, conference paper	Thothela et al. 2021); Serote et al., (2023); Abegunde et al. (2019); Mpakairi et al. (2023); Mashaba-munghemezulu & Chirima (2021);
Tanzania	5	Literature review	Mushi et al. (2022); Ayaz et al. (2019)
Ethiopia	7	Systematic review, geospatial analysis	Getahun et al. 2(024) Fetene (2021); Bayih et al. (2022)
Rwanda	5	Experimental design, case study	Kuradusenge et al. (2024); Chavula & Kayusi (2025)
Zambia	2	Quantitative survey	(Petros et al., 2025)

Mozambique	3	Spatial econometrics	Fang & Richards (2018)
Uganda	2	Preprint	Nomugisha & Mwebaze (2025)
Senegal	1	Project report	Beckie et al. (2022)
Malawi	2	Quantitative survey	Khoza et al. (2021)
Mali	1	Digital advisory service	Kante et al. (2019)
Burkina Faso	1	Quantitative survey, remote sensing	Karst et al. (2020)
Multi-country SSA	16	Systematic reviews, quantitative analysis	Bashiru et al. (2024); Onyango et al. (2021); Jellason et al. (2021); Choruma et al. (2024); Ayim et al., (2022); Rurii & Nzengya (2026); Zougmoré & Partey (2022); Appiah et al. (2025); Chisanga et al. (2025); Choruma et al. (2024); Lebourgeois et al. (2017); (Js et al. (2021); Klerkx & Rose (2020); Fabregas et al. (2019)

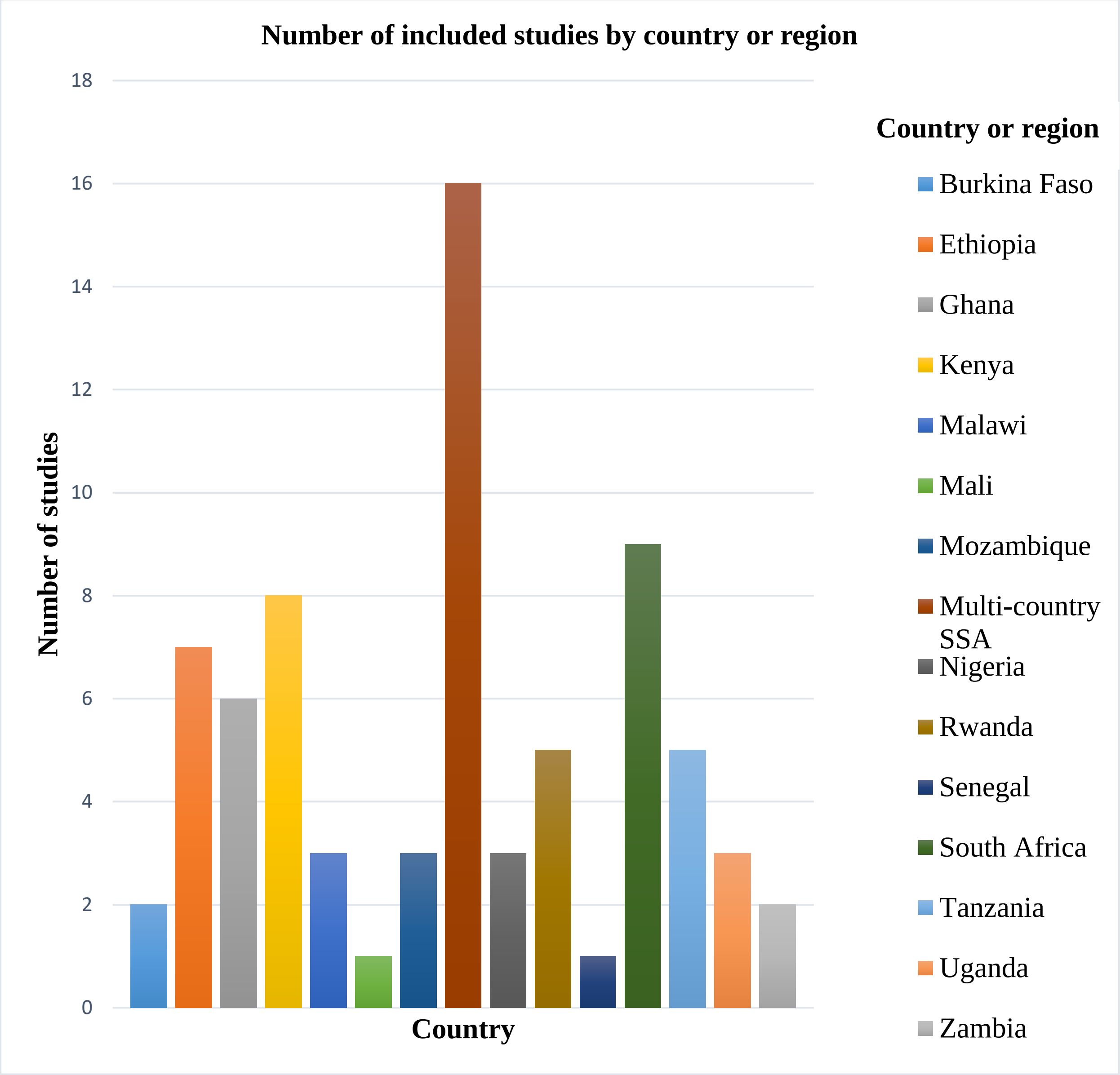

Fig 2: Number of studies by country

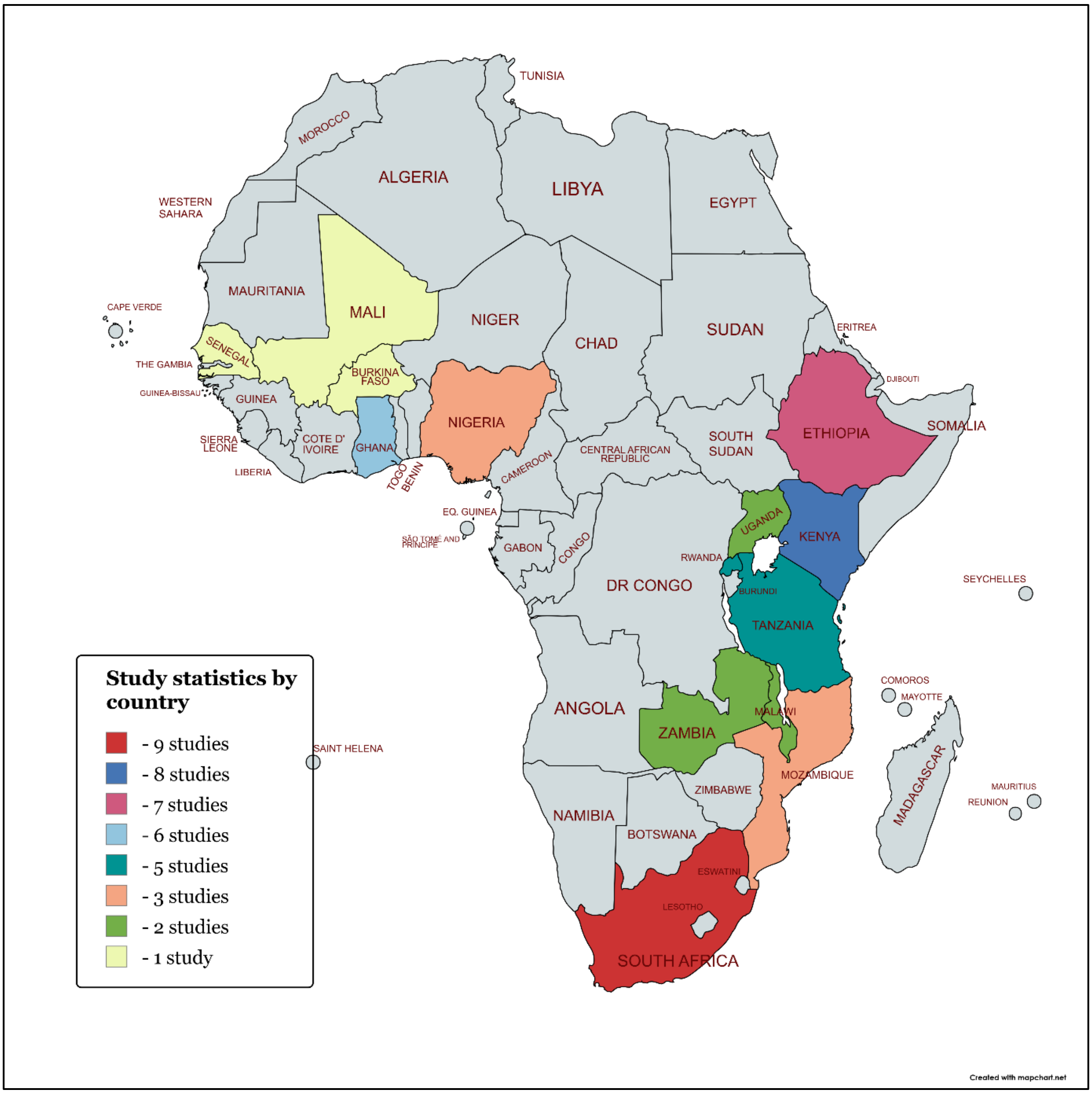

Figure 3: included studies by country

Source: MapChart. Africa: Create a custom map. Available online: [*https://www.mapchart.net/africa.html*](https://www.mapchart.net/africa.html) ***(accessed on 28 March 2026)***

3.2 Remote sensing, GIS and IoT technologies examined

Table 2: Technology types and applications

An overview of the main technology types examined in the review is provided in table 2. The table details the specific technologies, their respective application in the agricultural sector and examples of studies where they have been utilised.

Technology category	**Specific technology**	**Applications**	**Representative studies**
Remote sensing	Satellite imagery (Sentinel-2, Pléiades Landsat), drone-based sensors, multispectral imaging. CHIRPS, TAMSAT, SAR	Crop health monitoring (NDVI), yield prediction, land suitability analysis, rainfall monitoring, biomass estimation, invasive species detection, drought assessment.	Onyango et al. (2021); Manzi & Gweyi-Onyango (2021); Mmbando (2025); Bismark et al. (2021) (Nyaga et al. (2021); Ngulube (2025); Gatkal et al. (2024)' Rajka et al. (2023)
GIS-based tools	Spatial analysis software ArcGIS, QGIS, digital soil mapping, land suitability modeling, mobile GIS apps	Site-specific management recommendations, land-use planning, extension mapping services, resource allocation, water harvesting site selection, extensive service delivery mapping, and crop selection optimization.	Fetene (2021); Fang & Richards (2018)
IoT technologies	Soil moisture sensors, weather stations, automated irrigation systems,	Real-time monitoring, precision irrigation, climate data collection, automated control systems, network performance evaluation.	Kuradusenge et al. (2024); Bayih et al. (2022); Nomugisha & Mwebaze, (2025); Rajak et al (2023); (2018);Okoh et al.

	LoRaWAN networks, wireless sensors networks		(2023); Nigussie et al. (2020);
AI/Machine Learning	Random forest, neutral networks, productive analytics, disease detection algorithms, XGboost, deep learning, transformer models, casual ML	Yield prediction, pest/disease forecasting, advisory systems, pattern recognition, crop type mapping, field boundary delineation	Mmbando (2025); Nturo, Sumbiri, Ngugi, & Patrick (2025); Liakos et al. (2018); Foster et al (2023)
Digital advisory platforms	Mobile apps, SMS services, climate information services, decision support tools, chatbots, USSD	Information dissemination, personalized recommendations, extension support, weather forecasting, market linkages	Shaibu et al., (2025); Thothela et al. (2021); Asante et al. (2024); Abdulai et al. (2026)

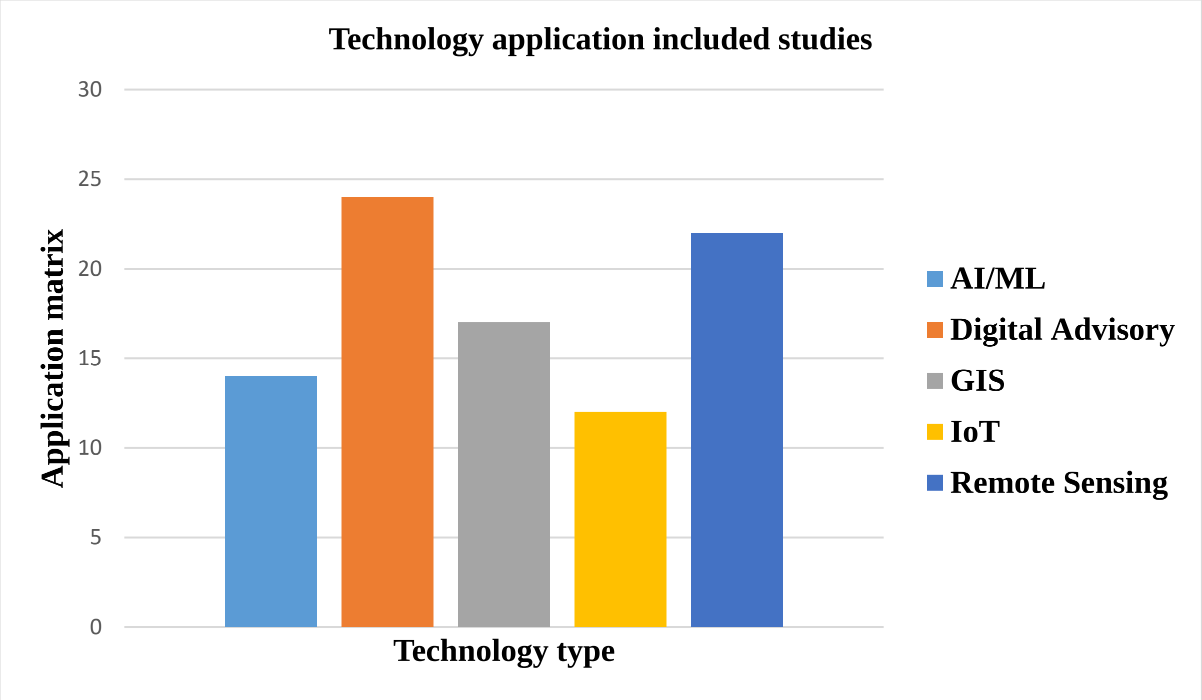

Figure 4: Technologies included in the study

Table 3: Technology application matrix

Title	**R/S**	**GIS**	**IoT**	**AI/ML**
AI-Driven Precision agriculture for Smallholder Farmers in Rwanda: A Case Study in Kayonza District 9Nturo, Sumbiri, Ngugi & Patrick (2025)	✓		✓	✓
Smart IoT Framework for Climate-Resilient and Sustainable Maize Farming in Uganda Nomugisha & Mwebaze (2025)			✓	✓
A survey of Intelligent Agro-climate Decision Support Tool for Small-Scale farmers: An Integration of Indigenous Knowledge, mobile Phone Technology and Smart Sensors Thothela et al. (2021)			✓	✓
Harnessing IoT and Data Analytics to enhance Resource efficiency and Crop Productivity in Smallholder Agriculture Hope & Mwebaze (2025)			✓	✓
Agro-ecological Lower Midland Zones IV and V in Kenya Using GIS and Remote Sensing for Climate-Smart crop Management Manzi & Gweyi-Onyango (2021)	✓	✓		

Harnessing artificial intelligence and remote sensing in climate-smart agriculture: The current strategies needed for enhancing global food security Mmbando (2025)	✓			✓
Precisions agriculture for resource use efficiency in smallholder farming system in Sub-Saharan Africa: A systematic review Onyango et al. (2021)	✓	✓	✓	
Smart farming technologies for sustainable agriculture: A review of promotion and adoption strategies by smallholders in sub-Saharan Africa Bashiru et al. (2024)	✓	✓	✓	✓
Agriculture 4.0: Is Sub-Saharan Africa Ready? Jellason et al. (2021)			✓	✓
Adoption of ICT innovations in the agriculture sector in Africa: A review of the literature Ayim et al. (2022)			✓	
IoT and machine learning-powered crop yield prediction system for smallholder farmers in Rwanda Kuradusenge et al. (2024)			✓	✓
Utilization of Internet of things and wireless sensors network for sustainable smallholder agriculture Bayih et al. (2022)	✓		✓	
Geographic information and communication technologies for supporting smallholder agriculture and climate resilience Haworth et al. (2018)	✓	✓		
Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk Ayaz et al. (2019)			✓	
Internet of Things in agriculture: Recent advances and future challenges Tzounis et al. (2017)			✓	
Machine learning in agriculture: A review Liakos et al. (2018)				✓

Digital technology and services for sustainable agriculture in Tanzania: A literature review Mushi et al. (2022)			✓	
Agricultural land suitability analysis for maize crop by using GIS technology in case of Debub Gondar Zone, Ethiopia Fetene (2021)		✓		
A new maize variety adoption in Mozambique: A spatial approach (Fang & Richards, 2018)		✓		
Comparing farmers perceptions of climate variability with meteorological and remote sensing data: implication for climate-smart agriculture technologies in Ghana Bismark et al. (2021)	✓			
Precision agriculture technologies for sustainable crop production in Ethiopia: A systematic review Getahun et al. (2024)	✓	✓	✓	
Improving smallholder farmers' access to and utilization of climate information services in sub-Saharan Africa through social networks: A systematic review Appiah et al. (2025)			✓	
Developing of IoT Cloud-based Platform for Smart farming in the Sub-Saharan Africa with Implementation of Smart-irrigation as Test-Case Okoh et al. (2023)			✓	
Digitalisation in agriculture: A scoping review of technologies in practice, challenges, and opportunities for smallholder farmers in sub-Saharan Africa Choruma et al. (2024)	✓	✓		
Digital innovations for climate-smart agriculture in East Africa: A systematic review Zegeye et al. (2017)	✓	✓	✓	✓
IoT-Based Irrigation Management for Smallholder Farmers in Rural Sub-Saharan Africa Nigussie et al. (2020)			✓	

Monitoring climate trends with remote sensing for evidence-based targeting of climate-smart agriculture technologies Muthoni (2023)	✓		✓	
Promoting the Adoption of Climate-Smart Agricultural Technologies Among Maize Farmers in Ghana Asante et al. (2024)				✓
Digital Technology and Services for Sustainable Agriculture in Tanzania: A Literature Review Mushi et al. (2022)		✓	✓	
The welfare of enhancing effects of agricultural innovation platforms and soil monitoring tools on farming households outcomes in southern Africa Abebe, Ann, et al. (2023)				✓
Digitization of African agriculture Tsan et al. (2019)	✓		✓	✓
A review of applications of remote sensing towards sustainable agriculture in Northern savannah regions of Ghana Moomen et al. (2024)	✓			
Evaluating utility of medium-resolution spatial Landsat 8 multispectral sensors in quantifying aboveground biomass Dube & Mutanga (2015)	✓			
Integration of optical and synthetic aperture radar imagery for cop mapping in Burkina Faso Forkuor et al. (2014)	✓			
Spatial variability and mapping of soil fertility status in a high-potential smallholder farming area under sub-humid conditions in Zimbabwe Soropa et al. (2021).	✓			
Analysis of land use/land cover changes and implications on crop production in South Africa Wang et al. (2023)	✓		✓	
Examining the potential of sentinel-2 MSI spectral bands in estimating maize biophysical variables Sibanda et al. (2015)	✓			

A GIS-based multi-criteria evaluation for rainwater harvesting suitability in Awi Zone , Northwestern Ethiopia Fetene et al. (2026)		✓	✓	
Kenyan Counties Geospatial Data Knowledge to Monitor Crop Production Wahome et al. (2023)		✓	✓	
Smart IoT-driven precision agriculture : Enhancing macro and micro nutrition efficiency and sustainability in modern agriculture and greenhouses Pelekamoyo et al. (2026)				✓
Exploring the capability of high - resolution satellite data in delineating the potential distribution of common invasive alien plant species in the Tshivhase Tea Estate Nembambula et al. (2023)	✓			
LoRaWAN-based IoT networks for smallholder agriculture in Kenya Nigussie et al. (2020)				✓
GIS-based assessment of climate-smart agriculture adoption determinants in South Africa Khoza et al. (2021)			✓	
Remote sensing and GIS for mapping agricultural drought vulnerability in Ethiopian highlands Fetene (2021)	✓		✓	
A framework for IoT-based precision irrigation for smallholder farmers in East Africa Nigussie et al. (2020)				✓
The role of GIS in optimizing crop selection for climate-smart agriculture in South Africa Fetene (2021)			✓	
The digitization of agriculture in Africa: A scoping review Choruma et al. (2024)	✓		✓	✓
Precision agriculture for smallholder farmers in sub-Saharan Africa Onyango et al. (2021)	✓		✓	✓
The role of digital technologies in enhancing climate resilience among smallholder farmers in SSA Mollel et al. (2025)	✓		✓	✓

GIS applications in agricultural extension services in Kenya Ayim et al. (2022)	✓		
A review of practices of big data analysis in agriculture Liakos et al. (2018)			✓
Internet of things for precision agriculture in sub-Saharan Africa Tzaunis et al. (2017)		✓	

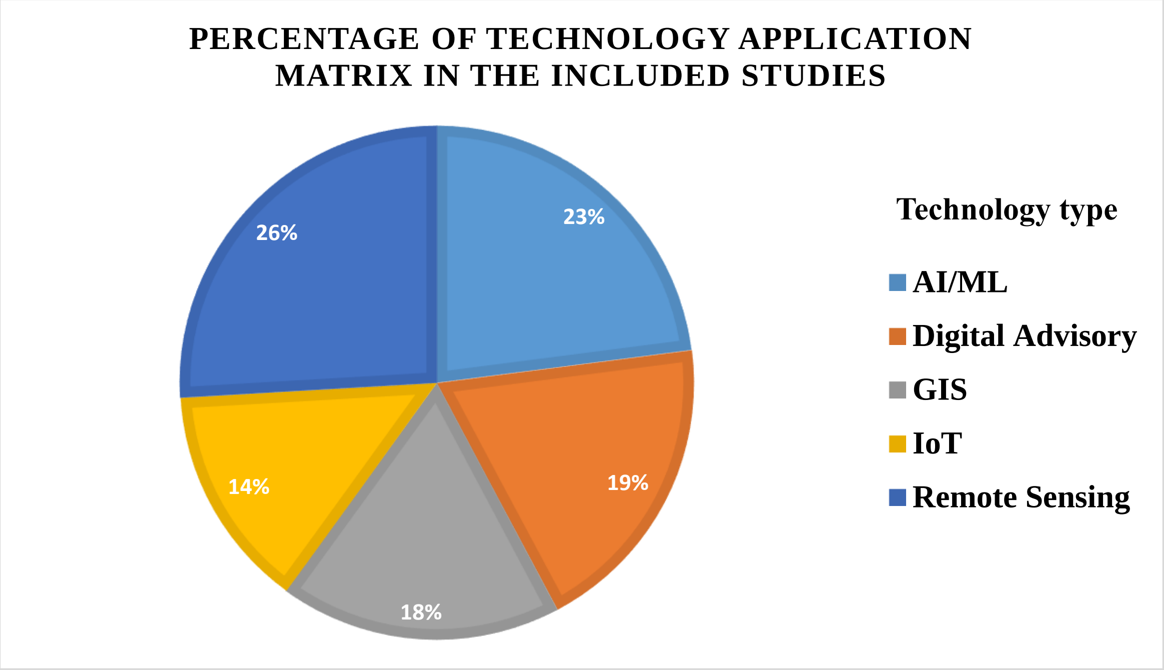

Figure 5: Technology application matrix by percentage

3.3 Technology application trend in SSA

The graph shows a clear upward trajectory with a notable surge after 2023 in sub-Saharan Africa. This aligns with the global shift towards agriculture 4.0; climate-smart digital solutions; and increased investment in agri-tech for smallholder farmers.

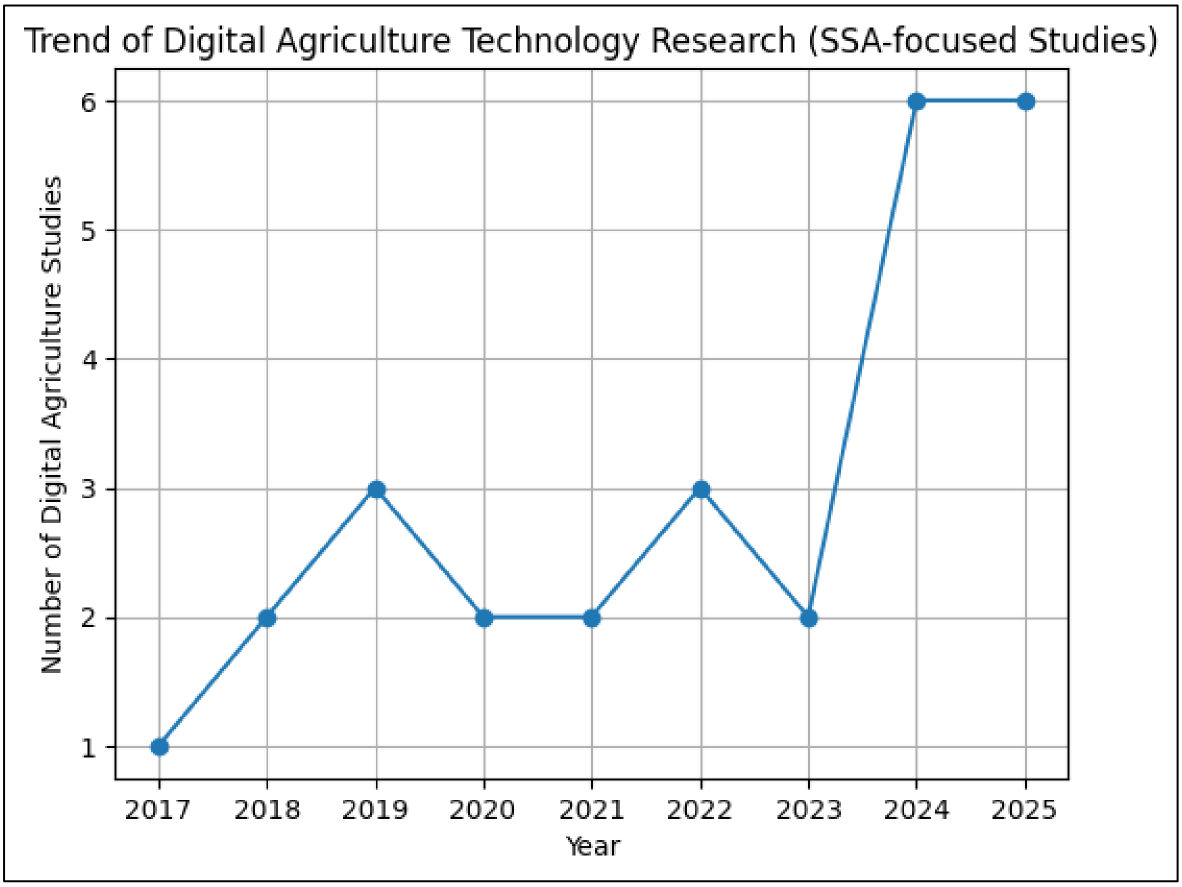

Figure 6: Digital agriculture technology trends in sub-Saharan Africa

Note: The graph indicates number of relevant publication per year plotted as a time trend

3.4 Quality assessment of included studies

The quality of included studies was assessed using adapted criteria from the Risk-Of-Bias Visualization (ROBVIS) checklists (Mcguinness, 2020). Studies were rated as low risk (n = 69), some concerns (n = 12) or high risk (n = 0) based on the methodological rigor, sample representativeness, and clarity of reporting. The four high-risk studies Tzounis et al. (2017); Liakos et al. (2018) are global-focused reviews, which provide contextual background but are not directly applicable to SSA-specific conclusions. Low quality (high-risk) studies were retained but given less weight in the synthesis.

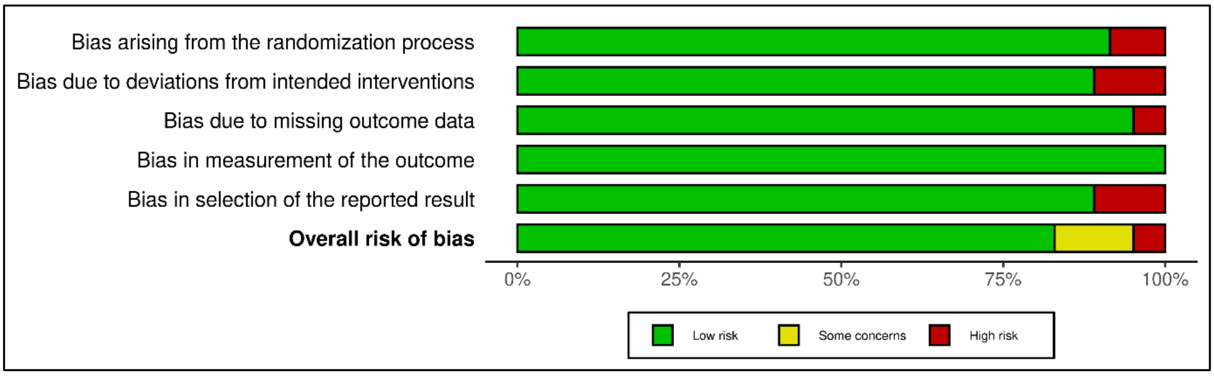

Fig 8: A summarized visual representation of risk of bias for included studies

Note: A number of studies among those rated as "some concerns" are foundational studies focusing on digital technologies in question among smallholder farmers at a global scale.

3.4 Influence on decision-making processes

The synthesis reveals three pathways through which remote sensing, geographic information systems and internet of things technologies influence smallholder farmers decision-making for Climate-smart agriculture adoption. These pathways operate at different temporal scales and address different types of agricultural decisions.

3.4.1 Pathway 1: Provision of real-time information

IoT-based systems and remote sensing technologies provide continuous, real-time data on soil parameters, microclimate conditions, and water availability (Rajak et al., 2023; Gatkal & Sharma, 2024). This information enables farmers to make evidence-based decisions about irrigation timing, fertilizer application, and planting schedules. Kuradusenge et al. (2024) developed an IoT and machine learning-powered crop yield Prediction System in Rwanda, demonstrating how real-time soil moisture and environmental data enabled precision irrigation decisions, leading to improvement in water use efficiency.

Bayih et al. (2022) designed an Agricultural Decision Support System that integrates Wireless Sensor Networks, Citizen Science, and remote sensing in Ethiopia, demonstrating hoe real-time data influence farmer decisions through mobile platform context-aware recommendations delivery. Okoh et al. (2023) implemented an IoT cloud-based platform for smart farming in sub-Saharan Africa, with smart-irrigation as a test case, indicated how real-time sensor data influenced irrigation scheduling decisions. Nomugisha & Mwebaze (2025) proposed a smart IoT framework, for climate-resilient maize farming in Uganda, showing how real-time monitoring can guide planting and input decisions. A review by Mushi et al. (2022) validates the pathways proposed by Nomugisha & Mwebaze (2025) and contextualizes wider hurdles that such frameworks face in Sub-Saharan Africa (Ngulube, 2025).

Influence mechanism: Continuous data streams → situational awareness → evidence-based adjustments → optimized resource use.

3.4.2 Pathway 2: Risk assessment through predictive analysis

Machine learning algorithms and remote sensing data enable crop health, disease prevalence and yield potentials diagnosis and assessments whereas AI-powered analytics forecast weather patterns and pests invasions (Foster et al, 2023; Gatakal & Sharma, 2024). The information is useful in supporting strategic decisions about selection of variety, planting dates and resource allocation. Mmbando (2025) reviewed how artificial intelligence and remote sensing in climate-smart agriculture support early warning systems and risk assessment, allowing proactive decision-making that reduces crop loses. Shaibu et al. (2025) examined how climate information services influenced smallholder farmers' willingness to invest in CSA practices in Northern Ghana, noting that access to daily or seasonal weather forecast shapes investment decisions through improved risk perceptions – farmers with forecast access were 2.3 times more likely to invest in drought-tolerant varieties. The potential of digital advisory services in this context further is supported by Asante et al. (2024) who demonstrated that that digital advisory services with predictive information significantly increased adoption of recommended CSA practices among smallholder farmers in Ghana. Nturo et al. (2025) developed an AI-driven precision agriculture system in Rwanda, demonstrating how predictive analytics enable farmers to make informed decisions about planting times and input application, with participating farmers reporting improvement in yield. Liakos et al. (2018) demonstrated that machine-learning techniques such as Random Forest Support Vector Machine and Artificial Neural Network could achieve high accuracy in yield prediction when calibrated with local dataset.

Influence mechanism: Historic → real-time data → predictive analytics → risk forecasting → strategic planning → proactive adaptation

3.4.3 Pathway 3: Timing through optimized scheduling and early waring

Integrated systems combining indigenous knowledge with sensor data and predictive analytics avail specific recommendations regarding when to plant, irrigation, harvest or input application, while early warning systems enable proactive response to climate variability (Oyelami et al., 2023). Thothela et al. (2021) surveyed intelligent agro-climate decision support tools for small-scale farmer, focusing on systems that integrate indigenous knowledge, mobile phone technology, and smart sensors. The study highlighted ITIKI system for drought prediction as a successful example, incorporating both indigenous observations and sensor data to influence farmer decisions. Farmers using ITIKI reported reduction in drought-related crop losses Shaibu et al. (2025); Dadzie et al. (2024) found that both scientific forecast and indigenous prediction shaped farmers decisions, with integration of both knowledge sources proving more effective than either alone - farmers receiving integrated information were more likely to adopt recommended practices. Nyoni et al. (2024) conducted a review on designed effective digital-based information service delivery of climate information for smallholder farmers, identifying that timing-specific recommendations achieved higher adoption rates than general advisories. additionally, Rurii & Nzengya (2026) carried out a scoping review on the adoption and impacts of climate-smart technologies in Africa, both identifying that support tools providing actionable timing guidance significantly outperformed information only approach thus reinforcing the influence of agricultural technologies on farmers' decision-making.

Influence mechanism: integrated knowledge systems (indigenous + scientific) → localized recommendations → actionable timing guidance → precise implementation.

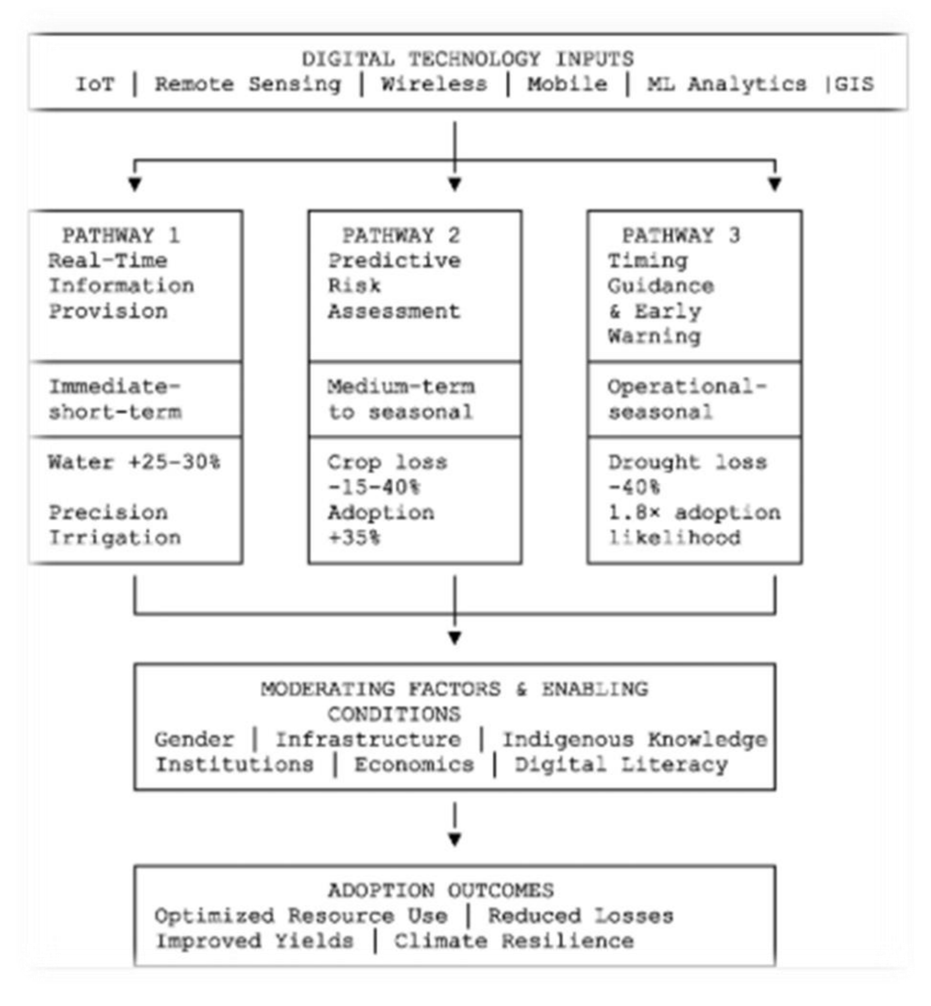

Figure 9: Integrated framework of digital technology influence pathways

3.5 Adoption determinants: Enablers and barriers

The review summarised findings on the key factors affecting adoption of agricultural technologies and presents a dual perspective, including enablers that drive adoption, and barriers that constraint it across seven categories (Teklu et al., 2022; Diro et al., 2022; Musfiri et al., 2022). The framework illustrates the multifaceted nature of adoption decisions and the range of factors that need consideration in the implementation strategies (Geels, 2019; Kreft et al., 2023).

Table 4: Adoption determinants across studies

Factor category	Enablers	Barriers	Representative studies
Technological	Real-time data availability, user friendly interfaces, mobile compatibility, integration with indigenous knowledge, demonstrated effectiveness	High costs, technical complexity, maintenance challenges, lack of user-friendly design, incompatible platforms	Onyango et al. (2021); Kuradusenge et al. (2024); Ayaz et al. (2019)
Infrastructural	Mobile network coverage, internet connectivity, access to stable electricity, LoRaWAN deployment, solar-powered solutions	Poor rural connectivity, unreliable power , high data costs, limited broadband infrastructure, network dead zones	Cariolle (2021); Jellason et al. (2021); Tzounis et al. (2017)
Economic	Credit access, subsidies, household income diversification, off-farm income, cost-sharing mechanisms,	High initial investment, poverty constraints, limited credit access, unaffordable data plans, unpredictable return on investment	Bashiru et al. 2024); Adenubi et al. (2021); Onyango et al. (2021)

	pay-as-you-go mechanisms		
Institutional	Strong extension networks, training programs, government support, multi-stakeholder partnerships, farmer cooperatives	Weak extension systems, limited technical support, policy gaps, inadequate funding, project-based rather than sustained support	Ayim et al. (2022) Abebe, Wheeler, Zuo, & Bjornlund (2023)
Social/ cultural	Farmer groups, social networks, alignment with local knowledge, peer learning, community champions	Resistance to change, mistrust of external information, language barriers, limited awareness	Thothela et al. (2021); Bismark et al. 2021); Shaibu et al. (2025); Mthethwa et al. (2022)
Gender	Women's group, gender-sensitive design, female extension agents, targeted training, flexible access models	Land tenure insecurity, restricted mobility, limited decision-making power, unequal access/ gender divide, time poverty	Khoza et al. (2021); Appiah et al. (2025)

Infrastructure barriers constitute the fundamental constraint. Cariolle (2021) analysed international connectivity and the digital divide in sub-Saharan Africa, she, and GSMA, (2021); Bontsaet al. (2023) noting that limited broadband infrastructure and high connectivity costs fundamentally constrain digital technology deployment. Similarly, Jellason et al. (2021) did an assessment of sub-Saharan Africa's readiness for agriculture 4.0 (fourth agricultural revolution transforming agricultural sector through integration of advanced digital technology), identifying poor digital infrastructure , unreliable electricity and high internet costs as the primary barriers to adoption of remote sensing, geographic information system and internet of things in the climate-smart agriculture. Mushi et al. (2022) documented similar finding with that of GSMA (2022) that even where mobile networks exist, data costs consume 5-15% of monthly household income, making data intensive applications unaffordable.

Economic barriers compound infrastructural limitations. Bashiru et al. (2024) found that high costs reduced uptake among resource-poor farmers, while access to credit increases chances of adoption by 2.5 times. Onyango et al. (2021) documented that precision agriculture technologies remain unaffordable for most smallholders, with basic sensor kits costing $200-500 - an equivalent to 3-6 months of income for average households. Nigussie et al. (2020) noted that while IoT-based irrigation systems demonstrated 30-50% water savings, initial costs prevented widespread adoption. On the other hand, Adenubi et al. (2021) noticed that whereas mobile phone penetration has increased, data costs remain prohibitive for data-intensive applications.

Institutional barriers cuts across categories, exacerbating systematic exclusion. In a systematic review on ICT adoption in African agriculture, Ayim et al. (2022) identified extension services as critical facilitators of ICT adoption in Africa, yet they note that most countries have extension to farmer ratios below 1:1,000, severely limiting reach. Onyango et al. (2021) identified technical skill gaps as a major barrier to precision agriculture adoption. Thothela et al. (2021) emphasized the need for training to enhance mobile phone technology potentials in South Africa. Abebe et al. (2023) found that innovation platforms and soil monitoring tools achieved impacts only when accompanied by sustained institutional support.

Gender constraints create systematic inclusion (Leta et al., 2023; GSMA, 2022). Khoza et al. (2021) conducted a gender-difference analysis of CSA adoption in Malawi and Zambia using extended Technology Acceptance Model and found that while perceived usefulness and ease of use of did not differ significantly between men and women when controlling for access, structural barriers including land tenure security, restricted mobility, and unequal access to credit constrained women’s adoption. In a similar pattern, Appiah et al. (2025) documented that women farmers have 30-50% lower access to digital agricultural services across Africa. Zougmoré & Partey (2022) found that gender-sensitive ICT interventions achieved higher adoption rates among women designed with their specific constraints in mind.

Integration of indigenous knowledge emerged as critical enabler (Oyalemi, 2023). Thothela et al. (2021) conducted a study and found that integration of indigenous knowledge with smart sensors and mobile technology enhanced decision support effectiveness and farmer acceptance. Bismark et al. (2021) compared farmer's perceptions of climate variability with meteorological and remote sensing data in Ghana, noting that the alignment between scientific and indigenous indicators increased trust and adoption. Shaibu et al. (2025) documented that farmers actively integrate both scientific forecast and indigenous predictions in their decision-making, regarding them as complementary rather than competing knowledge sources. Studies from west Africa, like Senegal, confirm similar patterns regarding the utilization of climate information (Beckie et al., 2022; Dibal et al., 2022).

3.6 The pilot-to-scale gap

A critical finding emerging from the synthesis is the persistent gap between successful pilot demonstrations and scalable, sustainable adoption (Kreft et al., 2023; Habiyaremye et al., 2024). Appiah et al. (2025) noted that among digital agriculture, initiatives mapped across Africa, fewer than 10% had reached more than 10,000 farmers, and less than 5% were financially sustainable without donor support. Rurii & Nzengya (2026) identified this pilot-to-scale gap as a principal challenge, finding that most projects are designed as technological demonstrations rather than systematic interventions. Jellason et al. (2021) further emphasize that without addressing foundational infrastructure deficits, scaling remains elusive.

Choruma et al. (2024) conducted a scoping review of agriculture, documenting that pilots typically focus on technical efficacy while neglecting the infrastructural, economic, and institutional environments required for sustained operation. The result is a landscape of pilot projects demonstrating potential without lasting impact, that is, the project terminates when funding ends, technical staff depart, or maintenance needs arise (McFodden et al., 2022; Habiyaremye et al., 2024).

3.7 Practices and adoption outcomes

Table 5: CSA practices influencing technologies, and adoption rates

The table presents a synthesised finding from the included studies on the influence of remote sensing, GIS-based tools and internet of things on stallholder farmers' decisions and the climate-smart agriculture adoption rates.

CSA practice	Adoption rate	Influencing technology	Representative study

Conservation agriculture	20-45%	Remote sensing for monitoring, GIS for sustainability mapping, IoT for soil moisture tracking	Brown et al., (2018); Partey et al., (2019); Ariom et al. (2022)
Drought-resistant varieties	40-60%	Climate information, predictive analytics, remote sensing for variety matching	Shaibu et al. (2025); Petros et al. (2025); Teklu et al. (2022)
Improved water management	20-50%	IoT sensors, smart irrigation, remote sensing for evaporation estimation	Kuradusenge et al. (2024); Bayih et al. (2022); Okoh et al. (2023); Nigussie et al. (2020)
Agroforestry	15-35%	GIS for land suitability, remote sensing for monitoring, digital advisories	Partey et al. (2019); Zougmoré & Partey (2022); Ewulo et al. (2025)
Integrated soil fertility	30-55%	Soil sensors, GIS mapping, digital advisories platforms, variable rate recommendations	Onyango et al. (2021)
Crop diversification	35-60%	Climate information, predictive analytics, market information systems	Amadu (2019); Waaswa et al. (2024); Dadzie et al. (2024)

Note: Adoption rates represents reported ranges across multiple studies; substantial variation exists based on context, technology type and enabling environment

4. SYNTHESIS

The synthesis of evidences form 56 studies across sub-Saharan Africa reveals complex landscape in which remote sensing, GIS, and IoT technologies hold significant promise for transforming smallholder agriculture, yet their actual influence on farmer decision-making remains constrained by deep-rooted structural barriers. The key findings show a cohesive understanding of how these technologies function, their operational pathways, and factors determining their adoption.

4.1 The influence pathways

Consistent evidences shows three distinct but integrated ways that the digital technologies influence farmers' decision-making. These pathways formulate a unified framework that explains how these technologies inform action at different temporal and strategic scales.

Pathway 1–real-time information provision operates at the immediate level. , IoT sensors, weather stations, and satellite imagery provide continuous streams of data that enable situational visibility. I this pathway, farmers who initially relied on guesswork are able to access precise information of when to irrigate their farms, the quantity of input such as fertilizers to apply to their crops, and whether the soil conditions are suitable for planting. Studies from Rwanda Kuradusenge et al. (2024), Ethiopia Bayih et al. (2022), Nigeria Okoh et al. (2023), and Uganda Nomugisha & Mwebaze (2025) collectively demonstrate that when farmers receive timely, localized data, they make decisions that are more efficient, precise and aligned with climate-smart principles. This pathway plays fundamental role in shifting farmers' decision-making from traditional-based to an evidence-based management

Pathway 2–risk assessment through predictive analytics operates at a strategic level. Machine learning algorithms applied to historical and real-time data forecast weather patterns, predict pest and diseases invasions, and estimate crop yield prior to harvest. This information assist farmer to make an informed decision on crop varieties, planting time, and efficient resource use. Mmbando (2025) presents a detailed review of how AI and remote sensing support early warning systems whereas Shaibu et al. (2025) presents empirical evidence indicating that access to seasonal forecast directly influence farmers' willingness to invest in climate-smart practices. This pathway transforms farmers from being reactive to proactive responders to climate shocks

Pathway 3–timing guidance through optimized scheduling and early warning, represent the most sophisticated integration of knowledge systems. It embodies combination of local knowledge accumulated over time with the modern sensor data and predictive analytics to generate specific recommendations about planting dates, irrigation timing, appropriate harvesting moments, and precise quantities of inputs application. The ITIKI system documented by Thothela et al. (2021) exemplifies this approach through a successful integration of indigenous drought indicators with artificial neural networks. Shaibu et al. (2025) further confirms that farmers do not choose between scientific and indigenous knowledge;

rather, they actively integrate both, thus, proving more effective in shaping their decisions. This pathway acknowledges that the technology must complement, not replace farmers' expertise. Put together, these pathways formulate a coherent framework crucial in understanding how digital technologies influence farmer decisions. For example, their operation, though different in time and scale (immediate, seasonal and strategic), address different types of agricultural decisions. These technologies are not mutually exclusive in their operation; however, an effective intervention needs to integrate all the three to create a comprehensive decision-support system that guide farmers from planning through execution.

4.2 Adoption determinant matrix: enablers and constraints

Whereas the pathways show decision-influence mechanism of these technologies, adoption determinants reveals why they do not (Teklu et al., 2022; Diro et al et al., 2022), the review synthesizes four categories of factors that collectively models adoption outcome. These categories (infrastructural, economic, institutional, and gender) do not operate individually but constitute an interconnectedness system of hurdles to the influence of these technologies on farmers' decision-making.

Infrastructural barriers constitute the foundational constraint factor. Poor rural connectivity, high data costs and unreliable electricity are beyond inconveniences. Studies show that they are binding challenges that hinder technology uptake (Cariolle, 2021), (Jellason et al., 2021). This indicates that devoid of network coverage, IoT sensors cannot transmit data, absence of electricity jeopardizes operations of weather stations, and unaffordable data hinders farmers' access to advisory services. The cumulative effect is that infrastructural deficits creates digital divide informing the current geographic and economic marginalization.

Economic challenges complicate these infrastructural constraints, even in a situation where infrastructure exists, high costs of sensors, devices, and data plans means digital technologies are beyond the reach of most smallholders (Bashiru et al., 2024); (Onyango et al., 2021) ; (Nigussie et al., 2020). For instance, a basic IoT sensor kit costing $200-500 representing 3-6 months' income for the average household is beyond reach of many farmers. While credit access and subsidies may mediate the costs, their scarcity in rural areas is still widespread. These economic hurdles assert pressure of exclusion to the most needy (poor farmers highly vulnerable to the climate risks) of the benefits of precision agriculture

Institutional barriers cut across all categories worsening systematic exclusion. Strong extension services, training programs, and continuous government support are catalysts to digital technology development and farmer adoption (Ayim et al., 2022). Nevertheless, the evidence reveal frail extension systems, limited technical support, and disjointed policies across most of sub-Saharan Africa countries. Even in situations where technologies exist, farmers lack effective trainings on the use and maintenance support of the technologies.

Gender constraints cut across all other categories thus creating systematic exclusion. Khoza et al. (2021) demonstrate that low adoption rates for women originates not from the differences in perceived usefulness rather, from structural barriers such as land tenure insecurity limiting decision-making power, restricted mobility, hindering access to training, and skewed access to credit, mobile phones and extension services. Appiah et al. (2025) confirm that women across Africa have consistent lower access to digital agriculture service. Furthermore, Mushi et al. (2022), in their systematic review on ICTs for climate resilience, documented persuasive infrastructural and socio-economic barriers disproportionately affect the most vulnerable, including women. Therefore, gender is a multiplier of disadvantage that fuel all other barriers.

This synthesis recognizes that adoption decision is not determined by a single factor, but through the interconnectedness of multiple challenges. A farmer may have access to credit (economic enabler) but lacks network coverage (infrastructural barrier) hindering technological adoption for climate-smart agriculture. A female farmer may have a mobile phone (technological access) but lacks decision-making power over land use (gender barrier) inhibiting practical application of technological services to climate-smart technology. Thus, effective interventions must address the complexity through integrated approaches that simultaneously tackle multiple barriers.

4.3 Indigenous knowledge and technology integration

Multiple studies indicate the importance of incorporating indigenous knowledge with modern digital technologies not as a cultural sensitivity, but as a practical necessity to enhance effectiveness and adoption. Bismark et al. (2021) for instance, found that when scientific forecasts from remote sensing aligned with farmers' indigenous indicators, trust increased and adoption seamlessly followed. Similarly, Shaibu et al. (2025) documented that farmers actively integrate both knowledge sources in their decision-making processes, regarding them as complementary sources. The ITIKI platform Thothela et al. (2021) explicitly designed for the integration combines indigenous drought prediction with artificial neural networks, suggested technology design that begins with farmers' existing knowledge systems. This opens an opportunity for farmer active participation in the knowledge generation a principle embodied in the citizen science approach.

4.4 Project-level pilot-to-scale as designed failure

This review suggests that the pilot-to-scale problem is fundamentally a design problem. The persistent gap between the successful pilots and the limited scaling, documented by Rurii & Nzengya Daniel (2026); Appiah et al. (2025) and Jellason et al. (2021) reflect that most pilots are designed as technical demonstrations rather than systematic interventions. They focus on hardware and software while neglecting the infrastructural, economic, and institutional environments required for sustained operations. Projects are designed for efficacy demonstration rather than resilience and diffusion in real-world conditions of unreliable electricity, intermittent connectivity, limited technical support, and farmers with multiple competing demands.

Sustainable scaling requires designing for maintenance after funding ends, support after technical staff depart, adaptation to variable infrastructure, and affordability without subsidy. This requires building on existing institutions such as extension services, farmer cooperatives, local businesses rather than creating parallel structures that crumble when the project support withdraws.

5. DISCUSSION

5.1 Limited but demonstrable influence

This review confirms that remote sensing, GIS-based tools, and IoT technologies have a demonstrable but limited influence on smallholder farmer decision-making for climate-smart agriculture adoption in sub-Sahara Africa. The evidence supports three primary conclusions that technologies work under right and favorable conditions in that the three influencing pathways are empirically validated across multiple scenarios. The evidences points that in Rwanda, IoT-enabled precision irrigation changed farmers decisions (Kuradusenge et al., 2024). Studies conducted in Ethiopia showed that real-time data delivered via mobile platforms influenced fertilizer application Bayih et al. (2022), while in Ghana, seasonal forecasts shaped investment in drought-tolerant varieties (Shaibu et al., 2025). Similarly, Thothela et al., (2021) validated that ITIKI system provided drought prediction that reduced crop loss in South Africa. Thus, in set-ups where infrastructure exists, training are provided, technologies are accessible, affordable, and designed for local contexts; the technologies positively influence farmer decisions.

Secondly, conditions are rarely right for farmers because infrastructure limitations, economic constraints, institutional weaknesses, and gender disparities exclude majority of farmers from technology influence. Farmers who face high climate risks especially in remote areas of the region face exclusion from the benefits of these technologies in CSA adoptions, thus, creating a paradox such that the technologies that could help most vulnerable are less accessible to them. Finally, the potential of these technologies is substantial but conditional, with the evidences suggesting appropriateness of these technologies in sub-Saharan Africa farming context, but that their potential might only be realized when accompanied by simultaneous investment in enabling environments that make them accessible and enhance their utility Bashiru et al. (2024), hence the technologies are necessary but insufficient.

5.2 Vulnerability and exclusion paradox

The central paradox revealed by this review–farmers most vulnerable to climate change are those least likely to access the technologies that could help them adapt, revealed by this review, operates through multiple mechanisms. Geographically, the most climate-vulnerable farmers often live in remote areas with poorest infrastructure–precisely, where IoT sensors cannot connect and satellite cannot substitute for ground-level validation. Economically, the most resource-poor farmers cannot afford the technologies that would make their resource use more efficient. Institutionally, farers with weakest extension links are least likely to receive training in technology use (Ayim et al., 2022). In addition, socially, women farmers who face the greatest climate vulnerability due to their dependence on natural resources have the least access to digital to (Mushi et al., 2022) (Khoza et al., 2021). This paradox is a fundamental challenge to the premise that digital technologies can contribute to climate adaptation at scale. The point to note is that if the technology influence remains concentrated among better-resourced, well-connected, and male –dominated population, then it will widen rather than bridging the existing inequalities. Such scenarios end up assisting those who need help less while leaving behind those who actually need more help.

5.3 Infrastructure as prerequisite for technological deployment

The evidence from Cariolle (2021), Jellason et al. (2021) and Bashiru et al. (2024) establishes infrastructure as binding constraint. In the absence of connectivity, and data affordability, digital technology cannot function to achieve its effective use thus a profound challenge for intervention design. Too often, infrastructure is treated as an afterthought while the evidence points that it is a fundamental factor and must be regarded as a prerequisite investment without which, a technology deployment has no meaning. It then means that digital agriculture interventions cannot succeed in isolation from broader rural deployment. The technologies require investment in grid extension, renewable energy, broadband deployment, and connectivity infrastructure. This insight shifts the responsibility from agricultural ministries alone to a multi-sectoral collaboration involving energy, telecommunication, and infrastructure development. It also suggests that the most impactful investment may not be in the technologies themselves but in the enabling systems that make technology effectiveness possible.

5.4 Indigenous knowledge as an asset

A significant findings of this review reveals the need to reframe indigenous knowledge vis a vis digital technologies (Oyalemi et al., 2023; Ngulube, 2025). The literature consistently indicates that indigenous knowledge is not an obstacle to technology adoption but an asset that enhances it. Bismark et al. (2021) found that alignment between scientific and indigenous indicators increased trust and Shaibu et al. (2025) documents that farmers integrate both knowledge sources. Thothela et al. (2021); Abdulai et al. (2024)on the other hand, demonstrate that systems designed for integration achieve greater acceptance. These findings challenge the technology centric approach that elevate modern technologies as a replacement for local expertise. They further suggest that effective intervention treats indigenous knowledge as an anchor for building solutions and not as a barrier to overcome in the development and deployment of these technologies. This has practical implications for technology design such that algorisms can be trained on indigenous indicators. Interfaces could be designed to accommodate local classification systems, while advisory messages can be framed in terms that resonate with local understanding. The goal is to replace farmer expertise with algorithmic authority but to augment it so that it gives farmers better information without undermining their urgency (Ngulube, 2025).

5.5 Gender as multiplier hurdle

The gender analysis from Khoza et al. (2021), Appiah et al. (2025), Leta et al. (2023), and GSMA (2021) reveals that gender is not merely another variable but a multiplier of advantages that intensifies all other barriers. Female farmers face similar infrastructural, economic and institutional constraints as do men, but they face them more severely due to land insecurity, mobility restrictions and unequal access to resources. Importantly, Khoza et al. (2021) found that when controlling for access, there is no difference in perceived usefulness and ease of use among male and female farmers. This indicates that women are not inherently resistant to technology rather; they suffer systematic exclusion from access to these technologies and their enablers (GSMA, 2021; Leta et al., 2023). This perspective is supported by broader reviews on ICT adoption in Africa (Mushi et al., 2022; Ayim et al., 2022). The implication is that specific interventions designed to address structural barriers such as land rights, access to credit, mobile phone ownership, and extension contacts can bridge the gender gaps. The design of technology alone is insufficient and thus, must be accompanied by social and institutional changes that mirror gender differences in the region (Leta et al., 2023).

5.6 Designed failure of pilot-to-scale as the problem

This review suggest that the pilot-to-scale problem is primarily a design problem (Habiyaremye et al., 2024; Kreft et al., 2023). For example, the existing gaps between successful and limited scale is documented by Rurii & Nzengya (2026), Appiah et al. (2025), and (McFadden et al., 2022) showing that most pilots are designed as technical demonstrations. They overlooking the evidence that the project cannot survive in a real world of unreliable electricity, intermittent network connectivity, limited technical support, and farmers having multiple competing demands. Thus, the pilots are designed for efficacy and demonstration as opposed to resilience and diffusion. It is evident that sustainable scaling requires designing should consider future maintenance after the end of the funding, future support after retire of technical staff, adaptation to various infrastructures and affordability without subsidy. This requires building on existing institutions like extension services, farmer cooperatives, and local business unlike creating parallel structures that crumble when the project support withdraws (Habiyaremye et al., 2024).

5.7 Implication for policy and practice

The findings of this review has implications for policy and practice. For policy makers, the primary implication is that digital agriculture cannot be pursued in isolation from broader rural development context. Infrastructure development does not complement technology deployment; rather, it is prerequisite for technology. It is imperative that the policies prioritize rural electrification, broadband deployment, and connectivity infrastructure alongside technology promotion. The policy needs to address structural barriers such as land tenure inequalities, credit access, extension reforms that shape adoption.

The review suggest the implication for practitioners that the technology design must begin with farmers and not sensors. This calls for investing time in understanding local knowledge systems, involving farmers in participatory design, targeting interface with target users before deployment of the technology. The design must consider affordability, exploring low-cost sensors, pay-as-you-go models and shared access arrangements. It means integrating existing extension systems rather than bypassing their usefulness, training extension officers in technology use, and positioning technology as a tool for their work.

For researchers, the need for longitudinal research that tracks the technology influence over multiple seasons, comparative studies that identify contextual factors shaping access and failures, and action research that tests interventions in real-world scenarios. The evidence heavily relies on pilot studies and cross-sectional surveys; thus, the need for a research that tracks farers overtime and cross contexts to understand what works where and why.

5.8 Limitations

This review acknowledges several limitations. First, uneven geographic coverage, with Eastern and Southern Africa overrepresented relatively to Western and Central regions of sub-Saharan Africa. Central Africa's absence from single-country studies limits the generalizability of the findings across the region. Second, the peer review literature may have over represent successful pilots and underrepresent failures and implementation challenges introducing public bias. Third, most studies are cross-sectional, limiting understanding of sustained technology influence over multiple seasons. Fourth, heterogeneity of technology types, outcome measures, and methodological approaches limit comparability across studies and precludes meta-analyses. Finally, the rapid evolution of digital technologies means findings may require updating as technologies and adoption patterns evolve. These limitations suggests the need for longitudinal research to understand sustained potential impacts of these technologies on CSA adoption decisions across the region.

6. CONCLUSION

This systematic review confirms that remote sensing, GIS-based tools, and IoT technologies hold potential of positively influencing smallholder farmer decision-making for climate-smart agriculture adoption through well-documented pathways – real-time information provision, risk assessment through predictive analytics, and timing guidance via optimized scheduling. However, this influence is currently limited to small-scale piloting contexts and systematically excludes the most vulnerable farmers because of crosscutting infrastructural, economic, and institutional and gender barriers. The technologies work under enabling conditions, which evidently are not available for most smallholder farmers. For these technologies to substantively contribute to climate adaptation, it requires a fundamental shift in approach from technology-centric interventions to systemic investment in enabling conditions that make technology accessible, affordable, and sustainable. This calls for viewing infrastructure as prerequisite, indigenous knowledge as asset, gender equity as central and sustainability as a designed principle. Without such systematic approaches, digital technologies risk widening the gap they purport to address and neglecting those who need help the most while assisting those who need them less. The promise of digital agriculture for climate adaptation in sub-Saharan Africa remains genuine but conditional: realized only when technology development proceeds hand-in-hand with the structural transformations that make its benefits accessible to all.

CHAPTER VI: INTEGRATIVE DISCUSSION

6.1 Synthesis of empirical findings on CSA adoption

6.1.1 Variation in awareness-knowledge across practices

The reflection of awareness variation across CSA practices (47% to 100%) indicates interaction between local farming knowledge, extension effectiveness and characteristics of specific practice (Finizola e Silva et al., 2024). The universal awareness of intercropping (100%) and crop rotation (90.8%) aligns with the research by Marenya & Barrett (2007), who found that these practices are traditional and integral to smallholder farming systems, constituting indigenous knowledge passes across generations. Ogunyiola et al. (2022) stressed that traditional ecological knowledge is foundational for community-based farming systems, deeply rooted in local culture and practice. They note that the influence of traditional ecological knowledge on adoption of new agricultural technologies can act as an important enabler when effectively incorporated with CSA innovations, or it could be a hurdle when such technologies conflict with established knowledge systems.

The high awareness of agroforestry (90.3%) and rainwater harvesting (81%) indicates successful extension outreach for these practices (Kato et al., 2011). This finding is consistent with Partey et al. (2018) in Ghana, who reported 95% of farmers being aware of CSA concepts, with agroforestry and water management practices among the most widely recognized. The systematic review by Finizola e Silva et al. (2024) identified informational factors including training, access to extension, group membership, climate information and CSA awareness as consistently showing positive effects on CSA adoption decision. The high awareness suggests that initial awareness-raising efforts have been effective and extension can now shift focus toward deepening knowledge and addressing implementation barriers.

The modern awareness of clusters of eight practices (53.5% to 65.8%) indicates that extension and information services have reached approximately two-thirds of farmers, but one –third remains unaware (Ogada et al., 2021). This aligns with Teklewold et al. (2013) in Ethiopia, who found similar awareness levels for IMP and conservation agriculture, noting that practices requiring behavourial change typically exhibit lower awareness than hose with visible, immediate benefits. Khatri-chhetri et al. (2017) similarly demonstrate that awareness of CSA technology varies significantly across farmer groups based on socio-economic characteristics, demographic factors, geographic contexts, and access to extension services.

6.1.2 The three patterns of awareness-knowledge relationships

The identification of three distinct patterns in the awareness-knowledge relationship signify important implications for extension programming.

Pattern 1: awareness exceeding knowledge (superficial awareness) – rainwater harvesting exhibited the largest gap (81% aware vs 39% knowledgeable), followed by agroforestry (90% vs 66%), and Biofertilizers (65% vs 54%). Kato et al. (2011) document that while rain water harvesting was widely known in Kenya, detailed knowledge of construction, maintenance and irrigation with farming systems was limited to less than 40% of farmers. They attributed this to awareness campaigns that successfully conveyed "what" and "why" but failed to provide the "how." For these practices, extension must shift from awareness raising to skills training. This finding align with the work of Mulungu et al. (2025), who emphasized that ICT-based extension interventions require well-designed messaging and adequate user training to be effective. The FAO (2025) Zambia initiative demonstrated that behavior-responsive agricultural extension combining field demonstrations, participatory problem-solving, and peer exchange could successfully bridge the gap.

Pattern 2: knowledge exceeds awareness (hidden knowledge or terminology mismatch) – improved varieties (47% aware vs 675 knowledgeable) and soil fertility management (56% vs 65%) showed this patter. This highlights that farmers possess practical knowledge but do not recognize the formal technology. Marenya & Barrett (2007) explained that farmers often practice soil fertility management as part of traditional farming without labeling it as a distinct CSA practice. For improved varieties, Fisher & Carr (2015) documented that farmers had substantial knowledge of drought-tolerant maize varieties acquired through experience but did not recognize the term "improved varieties." Miehe (2025) further demonstrated that farmers' mental model of how improved seeds work – including inflated expectations about "miracle seed" – significantly influence their adoption decisions. Kosmowski et al. (2018) provided an empirical evidence that farmers' self-reports of improved varieties adoption can be highly unreliable, with DNA fingerprinting revealing large discrepancies compared to survey responses. The implication is that extension must align terminology with farmer language, explicitly connecting formal term to practices farmers already use, while also managing expectations realistically.

Pattern 3: Awareness and knowledge aligned – for the remaining eight practices, awareness and knowledge were closely aligned, suggesting that extension has effectively built both together. This represents an extension success story and suggests that the integrated approaches used for these practices could serve as models for addressing gaps in other practices. The systematic review by Finizola e Silva et al. (2024) confirms that integrated approaches combining multiple information channels and support mechanisms are most effective in promoting CSA adoption. Similarly, Amadu et al. (2020) showed in Malawi that program participation and external support have positively and statistically significant effects on CSA adoption, particularly for resource-intensive practices. Together, these studies confirm that integrated approaches combining multiple information channels and support mechanisms are most effective in prompting CSA adoption.

6.1.3 The knowledge-principles gap

The consistent gap between knowledge and understanding of principles, with the largest gap for intercropping (-59.2 points) and IMP (-32.0 points), water-efficient irrigation (-14.0) and soil fertility management (-18.0) indicates that even among farmers who know how to implement practices, fewer understand the underlying principles. This is consistent with knowledge hierarchy Krathwohl (2010) where deeper conceptual understanding requires learning that is more intensive. The particularly large gap for IMP suggests that this practice has complex underlying principles that are not easy to grasp through observation or simple instructions. Jellason et al. (2021) advocate for giving farmers a voice to speak for themselves, rather than having researches or development agents speak for them. Thus, they highlighted the needs for integrating farmers' voices through innovative participatory videos to enable better understating of farmers experience in the processes of innovation effective in designing interventions and promote adoption of innovation. Ogunyiola et al. (2022) argue that to effectively upscale CSA adoption, a system requiring synergic partnerships between scientific knowledge and farmers' traditional knowledge is crucial. They suggests that understanding of principles might be enhances when a new practice is connected to farmers' existing conceptual knowledge and framework. Bayala et al. (2021) demonstrated that successful CSA implementation requires fostering strong partnerships to co-design agricultural systems with farmers.

The positive gap for conservation tillage (+29.5 points) could suggests that farmers learn principles through observation of demonstrations plots without acquiring full procedural knowledge. They understand why minimum tillage works (soil moisture conservation, organic matter accumulation) but may not know all implementation steps. Achieving principle-level understanding requires intensive participatory approaches such as farmer field schools, demonstration plots, and long-term engagements. The exceptionally high correlation between awareness and knowledge suggests potential conceptual overlap between the two constructs or the respondents may not clearly distinguish between being aware of CSA practices, and possessing knowledge about the. Future studies may consider refining measurement scales to enhance discrimination between there dimensions. The weak correlation between knowledge and principles (r = 0.151) suggests that current extension approaches may be succeeding at building procedural knowledge but failing on conceptual understanding.

6.1.4 Gender dynamics: women as hidden innovators

The finding that women have significantly higher awareness, knowledge, and understanding of principles than men is particularly noteworthy given that older literature often reported male advantage (Doss & Morris, 2001; Ragasa et al., 2013). This result aligns with gender sensitive research by Nchanji et al. (2025), who found that women in eastern Uganda had greater access to and sustained use of improved common bean varieties. The possible attribution to this could be women's primary responsibility for food crops, their active participation in farmer groups and successful gender targeted extension programs.

From the findings of this study, several factors may explain the advantage of female gender. First, ma CSA practices relate to food crops, which fall within women's traditional domain of responsibility (Doss & Morris, 2001; Ragasa et al., 2013). Second, women's participation in farm groups and social networks might facilitate knowledge sharing Kristjanson et al. (2012) and Gulati & Magnan (2026) reported similar finding that women's agricultural networks are approximately 26% larger than men's, though these networks rarely overlaps with men's, signifying that women access different information sources. Third, extension services might have successfully targeted women through gender-sensitive programming in recent years (Nchanji et al., 2025). The systematic review by Finizola e Silva et al. (2024) identified group membership and social networks as important informational factors positively influencing CSA adoption. Mutenje et al. (2019) noted that women's bargaining power, drought shock, and access to CSA technology information positively influenced the probability of investing in CSA technology combinations.

However, the multinomial logistic regression showed in the study that being male increases the odd f being a moderate adopter relative to low adopter. This suggests that while women have higher awareness and knowledge, they face barriers in translating these into higher adoption levels. These barriers likely include limited to land, credit, and decision-making power (Tabe-Ojong et al., 2024). Nchanji et al. (2025) in Tanzania found that men dominated climate adaptation decision-making processes due to land ownership and control. Gulati & Magnan

(2026) provide a nuanced perspective, finding that in India, when men are connected to adopters, household demands rises, but when women have similar connections, demands fall – not from unequal access (women are often better connected) but from different interpretations. This is a suggestion that men amplify positive experiences and women are more attentive to downside risks.

6.1.5 Education as the strongest predictor

The powerful effect on education on all three levels of understanding (F = 749.78 for awareness) aligns with extensive literature (Asfaw & Admassie, 2004; Goni et al., 2025). The finding that secondary education presents a critical threshold – with farmers at this level having nearly triple the awareness of those with primary education – has important implications. This "tipping point" phenomenon suggests that secondary education provides literacy, numeracy and cognitive skills that enables farmers to access and process technical information. Kirui (2019) reinforced this finding, stating that post-primary education is by far the most important factor in the use of agricultural inputs, with secondary and post-secondary levels significantly increasing the use of improved seed varieties and fertilizers. Similarly, Ruzzante et al. (2021) confirmed that farmers education consistently and positively correlated with the adoption of agricultural technologies across diverse contexts.

The complete absence of awareness among less-educated farmers for four crucial practices (conservation tillage, cover cropping, soil fertility management, and water efficient irrigation) represent a critical equity concerns. Asfaw & Admassie (2004) warned that if extension services fail to reach less educated farmers, the technological divide might widen, exacerbating existing inequalities. This finding underscores the urgent need for low-literacy extension approaches including visual aids, demonstrations, oral communication in farmers' languages, and deeper learning, as recommended by multiple studies (Teklewold et al., 2013; Goni et al. 2025). The FAO (2025) Zambian initiative demonstrates that community-led learning and lead-farmer mentorship can effectively reach farmers regardless of education level. Collectively these studies provide robust evidence that secondary education and above – serves as a critical threshold for effective agricultural technology adoption.

6.1.6 Age and farming experience as key determinants

The linear repression results revealed that age was strongest negative predictor of awareness (β = -0.743) and knowledge (β = -0.682), indicating that younger farmers have significantly higher understanding. The finding that younger farmers in Zavala had significantly higher awareness, knowledge and understanding of principles of CSA practices aligns with broader literature on age and technology adoption. Ofori et al. (2020) found that younger farmers tend to adopt precision agriculture sooner than older generation of farmers. Katchova & Sun (2022) confirm this as they note that average age of a new and beginning producer in the United States is 47.1 years, challenging the common belief that most new entrants are in their 20s or 30s, but confirming that younger farmers remain more receptive to innovation. The multinomial logistic regression confirms this, with age significantly decreasing the odds of being in higher adoption categories (OR = 0.610 for moderate, OR = 0.391 for high).

Farming experience showed a positive but weaker effect ($\beta = 0.151$ for awareness; $\beta = 0.121$ for knowledge; $\beta= 0.277$ for principles), suggesting that while experience brings exposure; it does not necessary lead to deeper understanding without formal education. Similarly, Tham-Agyekum et al. (2025) demonstrated that among Ghanaian tomato farmers, experience primarily facilitated adoption of familiar, cultural, and mechanical practices, whereas formal education was critical for the adoption of more complex mechanical techniques. This distinction supports the argument that while experience provides valuable exposure, the deeper understanding of principles essential for adopting complex or novel practice is more strongly associated with formal education. This conclusion reinforces meta-analysis of Ruzzante et al. (2021) confirming education as consistent positive predictor of adoption and highlighted its complementary role with extension services, particularly for knowledge-intensive natural resource management practices. This finding supports the need for targeted approaches for different experience levels (Sisay et al., 2023). Thus the positive effect of farming experience on principles understanding ($\beta = 0.277$, $p = 0.017$) suggests that experience may contribute to conceptual understanding through trial and error learning.

6.1.7 The role of institutional support

The multinomial logistic regression reveals that cooperative membership was significant predictor of high adoption (OR = 1.693E-13, p = 0.026), and extension contact approached significance (OR = 0.008, p = 0.055). this supports the extensive literature on the importance of institutional support (Davis et al., 2020; Tabe-Ojong et al., 2024). Cooperatives facilitate adoption through collective action, shared resources, and mutual learning (Wainaina et al., 2016; Fischer & Qaim, 2010). The significance of cooperatives to adoption reveals that farmers belonging to cooperative membership often have better access to information, input and markets as reported by (Mengistu & Meressa, 2023). Studies in Ghana found that cooperative membership increased adoption of machinery by 38.4 % and row planting by 25.3% (Addai et al., 2022).

The near significance of extension contact suggests that while extension services are valuable, their reach and effectiveness may be limited. This aligns with findings from Mozambique of an evaluation of public extension services that found that access for small and medium-sized farms was less than 9% in 2014 and had dropped to less than 7% by 2020 (Gobeia et al., 2023). The effectiveness of extension depends not only on contact but also on quality, with participatory approaches being more effective than top-down models (Meijer et al., 2015; Mwangi & Kariuki, 2015).

6.1.8 Improved varieties paradox: a terminology mismatch

The striking finding of the improved varieties paradox – knowledge (67%) substantially exceeds awareness (47%) – is a critical methodological insight and need to be interpreted with caution. The composite measure (awareness OR knowledge) reveals true familiarity at 82.5%, indicating that the low awareness is largely a measurement issue, a phenomenon largely known as "improved varieties paradox" as evident is (Glover et al., 2016; Wineman et al., 2020). For instance studies such as Kosmowski et al. (2018) used DNA fingerprinting to validate farmers' self-report of sweet potatoes varieties in Ethiopia, finding that approximately 30% of improved varieties were misclassified as local, and 20% of local varieties were reported as improved. Similarly Wineman et al. (2020), reported that in Tanzania, only 70% of maize seed samples were correctly identified by farmers, with both false positive and negative each exceeding 14%. These errors directly translate to underestimates of awareness and adoption. Furthermore, Wossen et al. (2015) demonstrated that such measurement error biases welfare and impact estimates towards zero, implying that true awareness could be substantially higher than observed.

Conceptually, Wineman et al. (2020) argued that standard survey terminology fails to capture how farmers experiment with, rename, and integrates seeds overtime. The low awareness reported in this study suggests that the adoption gap maybe smaller than reported and the problem may be more about terminology alignment than lack of exposure. Extension program should explicitly connect formal terms to practices that farmers already use. Instead of assumption that farmers do not know about improved varieties, extension agents should ask about specific varieties names familiar to farmers.

6.1.9 The polarized distribution of farmers

the strongly bimodal distribution of farmers by awareness levels - with 15.0% at the very low end and 54.2% at the high end – has been documented by Kristjanson et al. (2012) in Kenya, attributed this phenomenon to network effects. Farmers in well-connected communities learn many practices together through social learning, while isolated farmers learn fewer. This suggests that extension may have reached some farmers very effectively but completely misses others. The 15% of farmers with very low awareness (0-3 practices) represent the highest priority for extension targeting, as they are completely disconnected from agricultural innovation systems (Suri & Udry, 2022). The meta-analysis by Amoussouhoui et al. (2024) found that an overall pooled adoption rate of only 39% posing challenges of scaling digital technologies. Addressing these challenges requires a shift toward inclusive participatory approaches.

6.1.10 Unidimensionality of perception

The finding that Rogers' five perceived attributes collapse into a single dimension explaining 99.8% of variance reveal that farmers in Zavala o not distinguish between relative advantage, compatibility, ease of use, trialability, and observability when evaluating CSA technologies. This result aligns with critiques by Glover et al. (2019) who argued that DOI's applicability in smallholder contexts is often assumed rather than empirically verified. Similarly, van Hulst et al. (2020) found that Mozambican farmers evaluated CSA technologies holistically rather than through differentiated attributes assessments. Our factor analysis provides evidence supporting these critiques. This unidimenstionality might be explained by several factors:

Low formal education levels (44% primary or less) may limit farmers' ability or inclination to engage in differentiated cognitive processing. The dramatic increase in CSA perception scores with education (2.56 for primary-education vs 4.98 for tertiary-education) supports this interpretation. The novelty of CSA in this context may mean farmers have not yet accumulated sufficient experience to develop nuanced perceptions. Most CSA practices have only been promoted for 5-10 years in the region. As Rogers (2003) noted, perceptions evolve with experience, and differentiated attributes may emerge over time. Culture factors may favor holistic thinking styles over analytic decomposition. Varnum et al. (2010) argues that social orientation (collectivism vs individualism) is the key driver of holistic vs analytic cognitive styles, not other factors like wealth, thus it strengthens causal link between collectivism and holistic cognition.

6.1.11 Perceived compatibility and trialability as key drivers

The strongest effect of perceived compatibility and trialability on adoption levels align with Rogers' (2003) theory and recent empirical work of Denashurya et al. (2023). The finding that compatibility had a stronger effect on moderate adoption and triability on full adoption suggests a temporal pattern: compatibility determines initial adoption, while trialability influence progression to full adoption. Compatibility is crucial because practices that fit with existing farming systems, values, and cultural norms require less disruption and adaptation (Kernecker et al., 2021; Mandipaza, 2025). In the context of smallholder farmers, with limited resources, practices that require major changes may be beyond their capacity. This finding suggests that extension programs emphasize how CSA practices align with practices and can be integrated gradually (Pedzisa et al., 2015). The strong effect of trialability on full adoption reflects the importance of experiential learning (Moyo & Salawu, 2017). When farmer can experiment with the practices on small scale, they in essence reduce risk, build confidence while learning through action (Ragasa et al., 2025). This suggests that the programs should provide an opportunities for on-farm trials, demonstration plots, and starter packs that allows farmers to test practices before committing to full adoption (Sseguya et al., 2021).

6.2 Synthesis of systematic review findings on digital agriculture

6.2.1 The influence pathways

Consistent evidences shows three distinct but integrated ways that the digital technologies influence farmers' decision-making. These pathways formulate a unified framework that explains how these technologies inform action at different temporal and strategic scales.

Pathway 1–real-time information provision operates at the immediate level. , IoT sensors, weather stations, and satellite imagery provide continuous streams of data that enable situational visibility. I this pathway, farmers who initially relied on guesswork are able to access precise information of when to irrigate their farms, the quantity of input such as fertilizers to apply to their crops, and whether the soil conditions are suitable for planting. Studies from Rwanda Kuradusenge et al. (2024), Ethiopia Bayih et al. (2022), Nigeria Okoh et al. (2023), and Uganda Nomugisha & Mwebaze (2025) collectively demonstrate that when farmers receive timely, localized data, they make decisions that are more efficient, precise and aligned with climate-smart principles. This pathway plays fundamental role in shifting farmers' decision-making from traditional-based to an evidence-based management

Pathway 2–risk assessment through predictive analytics operates at a strategic level. Machine learning algorithms applied to historical and real-time data forecast weather patterns, predict pest and diseases invasions, and estimate crop yield prior to harvest. This information assist farmer to make an informed decision on crop varieties, planting time, and efficient resource use. Mmbando (2025) presents a detailed review of how AI and remote sensing support early warning systems whereas Shaibu et al. (2025) presents empirical evidence indicating that access to seasonal forecast directly influence farmers' willingness to invest in climate-smart practices. This pathway transforms farmers from being reactive to proactive responders to climate shocks**.**

Pathway 3–timing guidance through optimized scheduling and early warning, represent the most sophisticated integration of knowledge systems. It embodies combination of local knowledge accumulated over time with the modern sensor data and predictive analytics to generate specific recommendations about planting dates, irrigation timing, appropriate harvesting moments, and precise quantities of inputs application. The ITIKI system documented by Thothela et al. (2021) exemplifies this approach through a successful integration of indigenous drought indicators with artificial neural networks. Shaibu et al. (2025) further confirms that farmers do not choose between scientific and indigenous knowledge; rather, they actively integrate both, thus, proving more effective in shaping their decisions. This pathway acknowledges that the technology must complement, not replace farmers' expertise.

Put together, these pathways formulate a coherent framework crucial in understanding how digital technologies influence farmer decisions. For example, their operation, though different in time and scale (immediate, seasonal and strategic), address different types of agricultural decisions. These technologies are not mutually exclusive in their operation; however, an effective intervention needs to integrate all the three to create a comprehensive decision-support system that guide farmers from planning through execution.

6.2.2 Adoption determinant matrix: enablers and constraints

Whereas the pathways show decision-influence mechanism of these technologies, adoption determinants reveals why they do not (Teklu et al., 2022; Diro et al et al., 2022), the review synthesizes four categories of factors that collectively models adoption outcome. These categories (infrastructural, economic, institutional, and gender) do not operate individually but constitute an interconnectedness system of hurdles to the influence of these technologies on farmers' decision-making.

Infrastructural barriers constitute the foundational constraint factor. Poor rural connectivity, high data costs and unreliable electricity are beyond inconveniences. Studies show that they are binding challenges that hinder technology uptake (Cariolle, 2021; Jellason et al., 2021). This indicates that devoid of network coverage, IoT sensors cannot transmit data, absence of electricity jeopardizes operations of weather stations, and unaffordable data hinders farmers' access to advisory services. The cumulative effect is that infrastructural deficits creates digital divide informing the current geographic and economic marginalization.

Economic challenges complicate these infrastructural constraints, even in a situation where infrastructure exists, high costs of sensors, devices, and data plans means digital technologies are beyond the reach of most smallholders (Bashiru et al., 2024; Onyango et al., 2021); Nigussie et al., 2020). For instance, a basic IoT sensor kit costing $200-500 representing 3-6 months' income for the average household is beyond reach of many farmers. While credit access and subsidies may mediate the costs, their scarcity in rural areas is still widespread. These economic hurdles assert pressure of exclusion to the most needy (poor farmers highly vulnerable to the climate risks) of the benefits of precision agriculture

Institutional barriers cut across all categories worsening systematic exclusion. Strong extension services, training programs, and continuous government support are catalysts to digital technology development and farmer adoption (Ayim et al., 2022). Nevertheless, the evidence reveal frail extension systems, limited technical support, and disjointed policies across most of sub-Saharan Africa countries. Even in situations where technologies exist, farmers lack effective trainings on the use and maintenance support of the technologies.

Gender constraints cut across all other categories thus creating systematic exclusion. Khoza et al. (2021) demonstrate that low adoption rates for women originates not from the differences in perceived usefulness rather, from structural barriers such as land tenure insecurity limiting decision-making power, restricted mobility, hindering access to training, and skewed access to credit, mobile phones and extension services. Appiah et al. (2025) confirm that women across Africa have consistent lower access to digital agriculture service. Furthermore, Mushi et al. (2022), in their systematic review on ICTs for climate resilience, documented persuasive infrastructural and socio-economic barriers disproportionately affect the most vulnerable, including women. Therefore, gender is a multiplier of disadvantage that fuel all other barriers.

This synthesis recognizes that adoption decision is not determined by a single factor, but through the interconnectedness of multiple challenges. A farmer may have access to credit (economic enabler) but lacks network coverage (infrastructural barrier) hindering technological adoption for climate-smart agriculture. A female farmer may have a mobile phone (technological access) but lacks decision-making power over land use (gender barrier) inhibiting practical application of technological services to climate-smart technology. Thus, effective interventions must address the complexity through integrated approaches that simultaneously tackle multiple barriers.

6.2.3 Indigenous knowledge and technology integration

Multiple studies indicate the importance of incorporating indigenous knowledge with modern digital technologies not as a cultural sensitivity, but as a practical necessity to enhance effectiveness and adoption. Bismark et al. (2021) for instance, found that when scientific forecasts from remote sensing aligned with farmers' indigenous indicators, trust increased and adoption seamlessly followed. Similarly, Shaibu et al. (2025) documented that farmers actively integrate both knowledge sources in their decision-making processes, regarding them as complementary sources. The ITIKI platform Thothela et al. (2021) explicitly designed for the integration combines indigenous drought prediction with artificial neural networks, suggested technology design that begins with farmers' existing knowledge systems. This opens an opportunity for farmer active participation in the knowledge generation a principle embodied in the citizen science approach.

6.2.4 Project-level pilot-to-scale as designed failure

This review suggests that the pilot-to-scale problem is fundamentally a design problem. The persistent gap between the successful pilots and the limited scaling, documented by Rurii & Nzengya Daniel (2026); Appiah et al. (2025) and Jellason et al. (2021) reflect that most pilots are designed as technical demonstrations rather than systematic interventions. They focus on hardware and software while neglecting the infrastructural, economic, and institutional environments required for sustained operations. Projects are designed for efficacy demonstration rather than resilience and diffusion in real-world conditions of unreliable electricity, intermittent connectivity, limited technical support, and farmers with multiple competing demands.

Sustainable scaling requires designing for maintenance after funding ends, support after technical staff depart, adaptation to variable infrastructure, and affordability without subsidy. This requires building on existing institutions such as extension services, farmer cooperatives, local businesses rather than creating parallel structures that crumble when the project support withdraws.

6.2.5 Study limitation

The study acknowledges several limitations throughout data collection and during analysis; first, the cross-sectional design captures understanding at a single point in time, limiting casual inference. Second, reliance on self-reported data may introduce bas and social desirability bias. Third, the small no formal education group (n = 7) limits statistical power for comparisons involving this group. Lastly, terminology issues may have led to underestimation of awareness for some practices, as demonstrated by the composite measures of the improved varieties.

CHAPTER VII: RECOMMENDATIONS AND CONCLUSION

7.1 Practical recommendation for extension

Adopt stage-specific approaches: for practices with high awareness but low knowledge (rainwater harvesting, agroforestry) focus on building technical skills through farmer field schools, demonstration plots, and hands-on training. For practices where knowledge exceeds awareness (improved varieties, soil fertility management) align terminology with farmer language, explicitly connecting formal terms to practices farmers already use. For practices were understanding of principles lags behind knowledge (IPM), focus on conceptual education about why practices work through experiments and field schools.

Leverage women as early adopters and opinion leaders: train women farmers as peer educators and demonstration hosts, ensure women's representation in cooperative leadership, address remaining barriers including land rights and access to credit and design women-friendly training schedules accommodating domestic responsibilities.

Implement stage-targeted extension: for older farmers (50+)emphasize labor-saving practices, visible short-term benefits and use respected community leaders as messengers; for middle-aged farmers (34-49) focus on integrated CSA packages, profitability, and long-term sustainability; for younger farmers (29-33) provide comprehensive technical training, support for accessing land and credit, and leadership opportunities.

Strengthen social capital and information networks: support formation and strengthening of farmers cooperatives, train peer facilitators within existing social networks, establish structured farmer-to-farmer learning programs, and create incentives for farmers who successfully train others.

Prioritize training on rainwater harvesting: based on the awareness-knowledge gap analysis, rainwater harvesting should be the top priority with programs develop demonstration sites for rainwater harvesting in each village and provide materials and technical support for rainwater harvesting structures.

Shift from awareness to knowledge transfer: current extension services are effective at creating awareness but ineffective at transferring implementation knowledge. Programs should shift from lecture-based dissemination to hands-on, practical training approaches including demonstration plots, farmer field schools, learn-by-doing workshops, and follow-up visits.

Integrate digital technology strategically: this calls for integrating existing extension systems rather than bypassing their usefulness; training extension officers in digital technologies and their use; positioning technology as a tool for their work; investing time in understanding local language; and involving farmers in participatory approaches.

7.2 Policy recommendations

Investment in secondary education as foundation for adoption: given the near-deterministic relationship between education and adoption, consider increasing secondary school completion rates should a prerequisite for agricultural transformation. Ministries of education and agriculture should coordinate to integrate CSA contents into secondary school curricula and establish school demonstration farms

Redesign extension for low-literacy farmers: for current farmers with limited education, extension materials must be redesigned for low-literacy audiences using visual aids, demonstrations, radio programs, mobile videos, and peer learning approaches

Address the technological divide: the complete absence of awareness among less-educated farmers for four critical practices represents an equity concern requiring policy attention. Extension services must be redesigned to reach all farmers regardless of education level.

Support gender responsive programming: policies should address land rights, access to credit, and women's participation in extension programs, while also developing programs to engage men who have lower awareness.

7.3 Recommendation for future research

First, Conduct **longitudinal studies** to track how awareness, knowledge, and principles evolve over time and how they influence adoption decisions. Second, use of **mixed method** to understand the processes underlying the quantitative patterns. Quantitative research could illuminate terminology issues and farmers mental models. Third, research need to conduct **experimental interventions** to test stage-specific interventions and determine casual effects on adoption. Fourth, undertake **comparative research** across different regions and contexts to identify which findings are universal and which are context-specific. Fifth, the research need to **investigate household dynamics** in adoption, including the roles of women's decision-making power and joint decision-making. Sixth, it is important that research **develop approaches** that capture gradation of understanding and use farmer-recognized terminology, including composite measures and field verifications. Finally, conduct **implementation science research** on scaling digital agriculture beyond pilot projects**.**

7.4 CONCLUSION

The study demonstrates that while awareness of CSA practices is relatively high among farmers in Zavala district, deep understanding of principles is limited, and adoption levels strongly stratified by education, age, gender, and cooperative membership. The near-perfect correlation between awareness and knowledge suggests education is the gateway to adoption, thus, without investment in education, true understanding and adoption of CSA practices will remain limited regardless of extension efforts.. The unidimenstionality of CSA perceptions challenges the universal applicability of Rogers' multidimensional framework and suggests that extension should focus on building overall positive perceptions. The finding that women have higher CSA perceptions and are more likely high adopters challenges conventional narrative and suggests that women represent an underutilized resource for peer education. The prominence of generational divide favoring younger farmers indicates that youths are drivers of adoption and need support. The three patterns of awareness-knowledge relationships provide a diagnostic framework for targeted extension interventions like skills training for practices with superficial awareness, terminology alignments for practices with hidden knowledge, and continued integrated approaches for aligned practices. The complete exclusion of farmers with only primary education from high adoption is a major equity concern. The improved varieties paradox demonstrates that terminology mismatch is not a minor artifact but a systematic measurement problem with profound implications for agricultural research and policy methods. Policy interventions must extend beyond technology promotion to address foundational educational and social inequalities. Investing in secondary education, redesigning extension for low-literacy farmers, leveraging women as early adopters, engaging youths, and prioritizing training on rainwater harvesting represent the most of promising pathways for acerbating CSA adoption and building climate resilience in Mozambique's smallholder farming systems.

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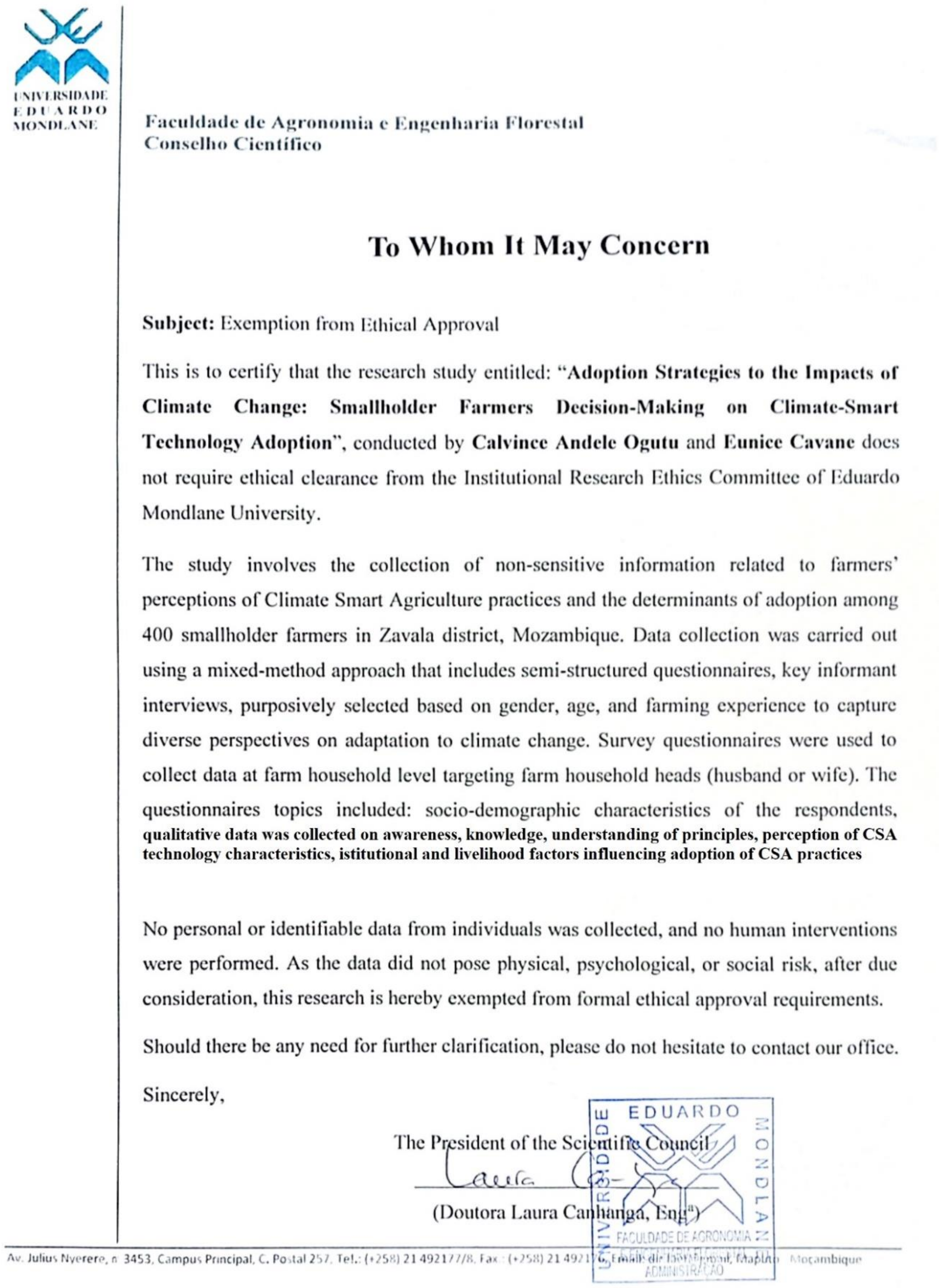
APPENDICES

Appendix 1: Ethical approval letter



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EDUARDO
MONDLANE

Faculdade de Agronomia e Engenharia Florestal
Conselho Científico

To Whom It May Concern

Subject: Exemption from Ethical Approval

This is to certify that the research study entitled: "**Adoption Strategies to the Impacts of Climate Change: Smallholder Farmers Decision-Making on Climate-Smart Technology Adoption**", conducted by **Calvince Andele Ogutu** and **Eunice Cavane** does not require ethical clearance from the Institutional Research Ethics Committee of Eduardo Mondlane University.

The study involves the collection of non-sensitive information related to farmers' perceptions of Climate Smart Agriculture practices and the determinants of adoption among 400 smallholder farmers in Zavala district, Mozambique. Data collection was carried out using a mixed-method approach that includes semi-structured questionnaires, key informant interviews, purposively selected based on gender, age, and farming experience to capture diverse perspectives on adaptation to climate change. Survey questionnaires were used to collect data at farm household level targeting farm household heads (husband or wife). The questionnaires topics included: socio-demographic characteristics of the respondents, **qualitative data was collected on awareness, knowledge, understanding of principles, perception of CSA technology characteristics, istitutional and livelihood factors influencing adoption of CSA practices**

No personal or identifiable data from individuals was collected, and no human interventions were performed. As the data did not pose physical, psychological, or social risk, after due consideration, this research is hereby exempted from formal ethical approval requirements.

Should there be any need for further clarification, please do not hesitate to contact our office.

Sincerely,

The President of the Scientific Council
Laura
(Doutora Laura Canhanga, Engª)

Av. Julius Nyerere, n 3453, Campus Principal, C. Postal 257, Tel.: (+258) 21 492177/8, Fax: (+258) 21 492176, Email: [illegible], Maputo Moçambique

Appendix 2: Data collection tool

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Farmer Climate-Smart Agriculture (CSA) Adoption Survey

Introduction: Hello, my name is …………………………………………......[Enumerator Name]. We are conducting a survey to understand farmers' knowledge, attitudes, and practices related to agricultural technologies and information sources. The information you provide will help improve agricultural extension services. Your participation is voluntary, and your responses will be kept confidential. The survey will take approximately 30-45 minutes.

Respondent ID: (Pre-filled from sampling list)
Date of Interview: [Date]
Enumerator Name: [Enumerator Name]

Section A: Farmer Demographics and Farm Characteristics

#	**Question**	**Response / Code**
A1	What is your age (in years)?	_______ (Years)
A2	Gender of the respondent.	Male .... 1 Female 0
A3	What is your highest level of education?	No formal education .... 0 Primary school 1

#	Question	Response / Code
		Secondary school .... 2 Tertiary/University 3
A4	How many years of experience do you have in farming?	_______ (Years)
A5	What is the total size of your farm?	_______ (Hectares)
A6	What are your main farm-related income activities?	Farming only .... 1 Farming and livestock .... 2 Farming and off-farm business/employment 3
A7	What is your primary source of income?	Farming .... 1 Livestock .... 2 Off-farm 3
A8	What was your approximate total annual income from all sources in the last year?	_______ (Local Currency)

Section B: Awareness of CSA Practices and Technologies

For each practice: Are you aware of :?

#	Practice / Technology	Aware (Yes = 1 / No = 0)
B1	Agroforestry (growing trees with crops)	
B2	Drought-tolerant crop varieties	
B3	Improved crop varieties (high-yield/disease resistant)	
B4	Conservation tillage (minimum/reduced tillage)	
B5	Integrated Pest Management (IPM)	
B6	Rainwater harvesting	
B7	Organic farming / composting	
B8	Intercropping	
B9	Crop rotation	
B10	Cover cropping	
B11	Bio-fertilizers / beneficial microbes	
B12	Soil fertility management (e.g., soil testing, integrated nutrient management)	
B13	Water-efficient irrigation (e.g., drip irrigation)	

Section C: Source of Knowledge for Practices

For each practice you are aware of, do you know how to use this practice? ***(Use 0 = No, 1 = Yes.)***

#	**Practice**	**Knowledge of use** ***(0 = No, 1 = Yes.)***
C1	Agroforestry	
C2	Drought-tolerant varieties	
C3	Improved varieties	
C4	Conservation tillage	
C5	Integrated Pest Management (IPM)	
C6	Rainwater harvesting	
C7	Organic farming	
C8	Intercropping	
C9	Crop rotation	
C10	Cover cropping	
C11	Bio-fertilizers	
C12	Soil fertility management	
C13	Water-efficient irrigation	

Section D: Principles Guiding the Use of Practices

For each practice you aware of, what is the main principle or reason guiding your use/interest in this practice? (Use the codes below.)

Principle Codes:

1 = Improves soil health
2 = Increases yield
3 = Reduces cost
4 = Conserves water
5 = Reduces pest/disease pressure
6 = Climate resilience (drought/flood)
7 = Other (Specify)
0 = Not Applicable / Not Used

#	**Practice**	**Principle Code**
D1	Agroforestry	
D2	Drought-tolerant varieties	
D3	Improved varieties	
D4	Conservation tillage	
D5	Integrated Pest Management (IPM)	
D6	Rainwater harvesting	
D7	Organic farming	
D8	Intercropping	

#	Practice	Principle Code
D9	Crop rotation	
D10	Cover cropping	
D11	Bio-fertilizers	
D12	Soil fertility management	
D13	Water-efficient irrigation	

Section E: Quality and Content of Agricultural Information

Rate the following statements about the agricultural information they receive on a scale of 1 to 5, (where 1=Very Poor and 5=Excellent.)

#	Statement	Rating (1-5)
E1	How would you rate the **overall quality** of the agricultural information you receive?	
E2	The information is provided in a **timely** manner (e.g., before the planting season).	
E3	The information is **accurate** and reliable.	
E4	The information is easy to **understand**.	
E5	The information is **relevant** to my farming needs.	

#	**Statement**	**Rating (1-5)**
E6	The information is **complete** (covers all I need to know).	
E7	The information is **consistent** across different sources.	
E8	The information I receive helps me make better **decisions** on my farm.	

How often do you receive information specifically about the following topics? Rate on a scale of 1 to 5, (where 1=Never and 5=Very Frequently.)

#	**Topic**	**Frequency (1-5)**
E9	Drought management	
E10	Flood management	
E11	Pest and disease control	
E12	Planting techniques/timing	
E13	Fertilizer application	

Section F: Sources of Agricultural Information

Which of the following sources do you use to get agricultural information? (Select all that apply.)

#	Source	Used (Yes = 1 / No = 0)
F1	Government Extension Agent	
F2	Radio	
F3	Mobile Phone (calls, SMS, apps)	
F4	Fellow Farmers	
F5	Farmer Cooperative/Group	
F6	Television	
F7	Internet (social media, websites)	
F8	Input Suppliers/Agro-dealers	
F9	NGOs (Non-Governmental Organizations)	
F10	Other (please specify)	

F11. In the last year, approximately how many times have you had contact with an extension agent? _______ (Number)

Section G: Trust in Information and Information Sources

Please rate your agreement with the following statements on a scale of 1 to 5, (where 1=Strongly Disagree and 5=Strongly Agree.)

#	Statement	Rating (1-5)
G1	I trust that the information I receive is based on sound **knowledge**.	
G2	I trust that the information sources are **reliable**.	
G3	I trust that the information providers are **honest**.	
G4	I feel **comfortable** asking questions to information providers.	
G5	I believe information providers **care** about my success as a farmer.	
G6	I trust that the information is **accurate**.	
G7	I believe information providers are **fair** in their dealings with all farmers.	
G8	I would **prefer to get information from extension agents** rather than other sources.	
G9	I trust that information providers will **follow up** on the advice they give.	
G10	Overall, I trust the agricultural information I receive.	
G11	I have had a **negative experience** with an information source that made me trust them less.	
G12	My trust in information sources would **increase if they were more open** about limitations/risks.	

Now, think about how trust in an information source affects your actions guided by following statements on a scale of 1 to 5, (where 1=Strongly Disagree and 5=Strongly Agree.)**.**

#	**Statement**	**Rating (1-5)**
G13	I am **more likely to adopt a practice** if I trust the source providing the information.	
G14	I trust that information from a trusted source leads to **higher quality results** on my farm.	
G15	I would be less likely to adopt a practice if I knew it had performed **poorly for a farmer I trust**.	
G16	I am more likely to **trust information that comes from a fellow farmer** than from other sources.	
G17	I am **less concerned about risks** of a new practice if I trust the source recommending it.	

Section H: Attitudes and Perceptions towards CSA Practices (Innovation Characteristics)

Think about the new farming practices you have heard about (like those in Section B). Please rate your agreement with the following statements on a scale of 1 to 5, (where 1=Strongly Disagree and 5=Strongly Agree.)

#	**Statement**	**Rating (1-5)**
H1	Using these practices **increases my crop yields** compared to my usual methods. (Relative Advantage)	

#	Statement	Rating (1-5)
H2	Using these practices helps me **reduce my farming costs**. (Relative Advantage)	
H3	These practices **fit well** with my current farming system. (Compatibility)	
H4	These practices are **compatible with my cultural practices** and beliefs. (Compatibility)	
H5	The practices are **easy to understand**. (Complexity - reversed)	
H6	The practices are **easy to use** and implement on my farm. (Complexity - reversed)	
H7	I have been able to **try these practices on a small scale** before fully adopting them. (Trialability)	
H8	I can easily **see the results** of these practices on other farmers' fields. (Observability)	
H9	Most people in my **community** think I should use these practices. (Social Norms)	
H10	My **family** thinks I should use these practices. (Social Norms)	
H11	I have the necessary **resources** (labor, time, knowledge) to use these practices. (Perceived Behavioral Control)	

#	Statement	Rating (1-5)
H12	I can **afford** to implement these practices. (Perceived Behavioral Control)	
H13	Using these practices will **increase my farm income**. (Attitude)	
H14	Using these practices is **good for the environment**. (Attitude)	

Section I: Adoption Intentions and Behavior

Please answer the following about your plans and current use.

#	Question	Response
I1	Do you **intend to adopt** any of these new practices in the next 12 months? (1=Yes, 0=No)	
I2	Would you **recommend** these practices to other farmers? (1=Yes, 0=No)	
I3	Have you **actually used any of these tools/technologies** on your farm in the past 3 years? (1=Yes, 0=No)	
I4	Do you feel there is enough **policy support** (e.g., subsidies, programs) for adopting these practices? (1=Yes, 0=No)	
I5	Do you **expect to succeed** if you fully adopt these practices? (1=Yes, 0=No)	

#	Question	Response
I6	Have you **seen these practices work** well on other farms? (1=Yes, 0=No)	
I7	Do you expect them to **increase your yields**? (1=Yes, 0=No)	
I8	Do you believe the **benefits** of adoption outweigh the costs? (1=Yes, 0=No)	

Section J: Risk Perceptions

Please rate your agreement with the following statements on a scale of 1 to 5, where 1=Strongly Disagree and 5=Strongly Agree.

#	Statement	Rating (1-5)
J1	New farming practices are generally **low-risk**.	
J2	I am willing to adopt new practices to **avoid potential failure** of my current methods.	
J3	I am willing to take risks to **seek higher profits** from my farm.	
J4	I would **adopt a new practice despite risks** if it has clear long-term benefits.	

Section K: Current Adoption and Support

#	**Question**	**Response / Code**
K1	Are you currently **considering adopting** any new farming practice? (1=Yes, 0=No)	
K2	Do you **intend to adopt a new practice in the next season**? (1=Yes, 0=No)	
K3	Have you received any **training** on new agricultural practices in the last 2 years? (1=Yes, 0=No)	
K4	How would you rate your **confidence** in successfully implementing new practices? (Scale 1-5, 1=Not confident, 5=Very confident)	
K5	Are you a member of a farmer **cooperative** or group? (1=Yes, 0=No)	
K6	How often do you **share advice** with other farmers? (1=Never, 5=Very Frequently)	
K7	How would you rate the current **soil fertility** on your farm? (1=Very Poor, 5=Excellent)	
K8	Do you have access to a reliable **water source** for irrigation? (1=Yes, 0=No)	
K9	Do you own any **irrigation equipment**? (1=Yes, 0=No)	

#	Question	Response / Code
K10	Do you have access to **farm tools and equipment**? (1=Yes, 0=No)	
K11	How frequently does your farm experience **climate-related shocks** (drought, flood)? (1=Never, 5=Very Frequently)	
K12	Have you received any agricultural **subsidies** (e.g., for seeds, fertilizer) in the last year? (1=Yes, 0=No)	
K13	How would you rate your access to **markets** to sell your produce? (1=Very Poor, 5=Excellent)	

Appendix 3: SDAE consent form

UNIVERSIDADE EDUARDO MONDLANE

Faculdade de Agronomia e Engenharia Florestal

GUIA DE MARCHA Nº 217 /FAEF/2025

Segue o estudante **Calvince Andele Ogutu,** da faculdade de Agronomia e Engenharia Florestal da Universidade Eduardo Mondlane, no período compreendido entre os dias **04 de Agosto á 03 de Setembro** do ano em curso, na província de Inhambane, no distrito de Zavala, no âmbito da recolha de dados do trabalho de Dissertação.

Serviços Administrativos da faculdade de Agronomia e Engenharia Florestal da Universidade Eduardo Mondlane em Maputo, ao **01 de Agosto de 2025.**

O Chefe da Secretaria

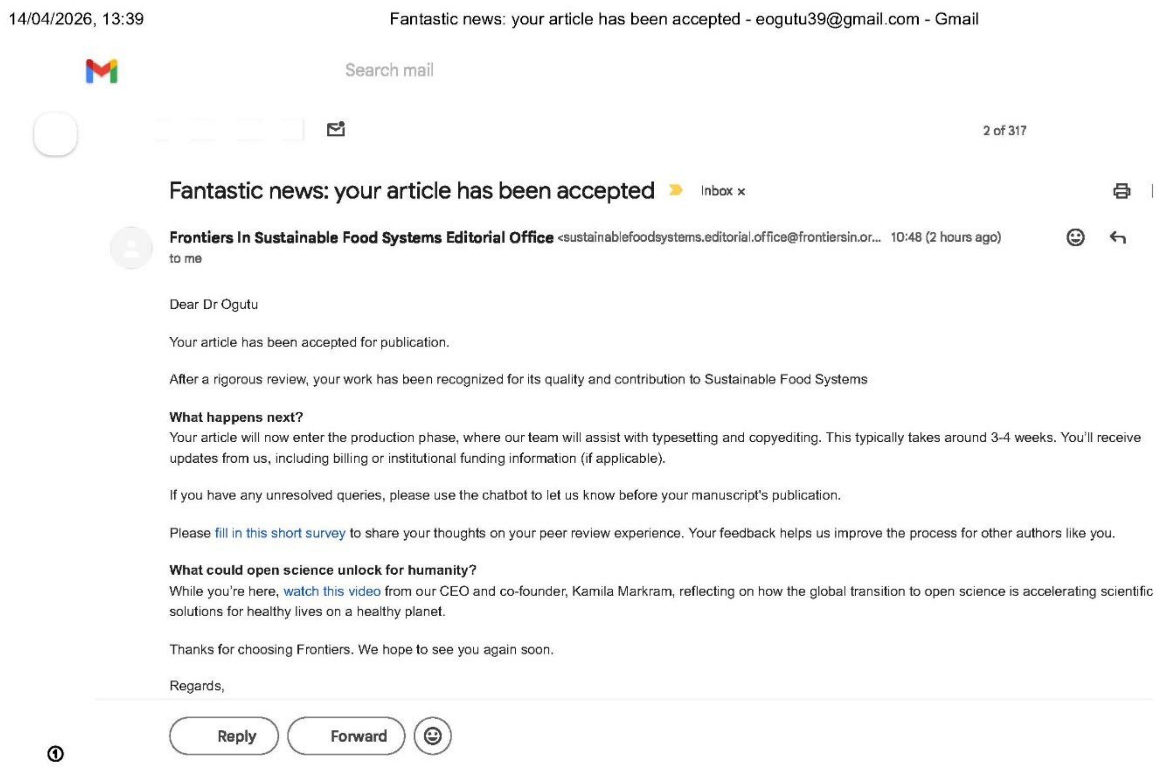
(Hilário A. Manguengue)

Apresentou-se neste S. D. A. E. de Zavala
Em 04/8/2025 e regressa à sua procedência 03/09/2025
O Chefe da Secretaria
Amélia Mariano 03.09.2025
Amélia

Recebido
04-08-25
Amélia

Av. Julius Nyerere, nº 3453 Campus Principal, C. Postal 257 Tel. (+258) 21 492177/8, Fax (+258) 21 492176 Email dir.faef@gmail, Maputo Moçambique

Appendix 4: Proof of Acceptance for manuscript II publication


14/04/2026, 13:39 Fantastic news: your article has been accepted - eogutu39@gmail.com - Gmail

Fantastic news: your article has been accepted

Frontiers In Sustainable Food Systems Editorial Office <sustainablefoodsystems.editorial.office@frontiersin.or... 10:48 (2 hours ago)
to me

Dear Dr Ogutu

Your article has been accepted for publication.

After a rigorous review, your work has been recognized for its quality and contribution to Sustainable Food Systems

What happens next?
Your article will now enter the production phase, where our team will assist with typesetting and copyediting. This typically takes around 3-4 weeks. You'll receive updates from us, including billing or institutional funding information (if applicable).

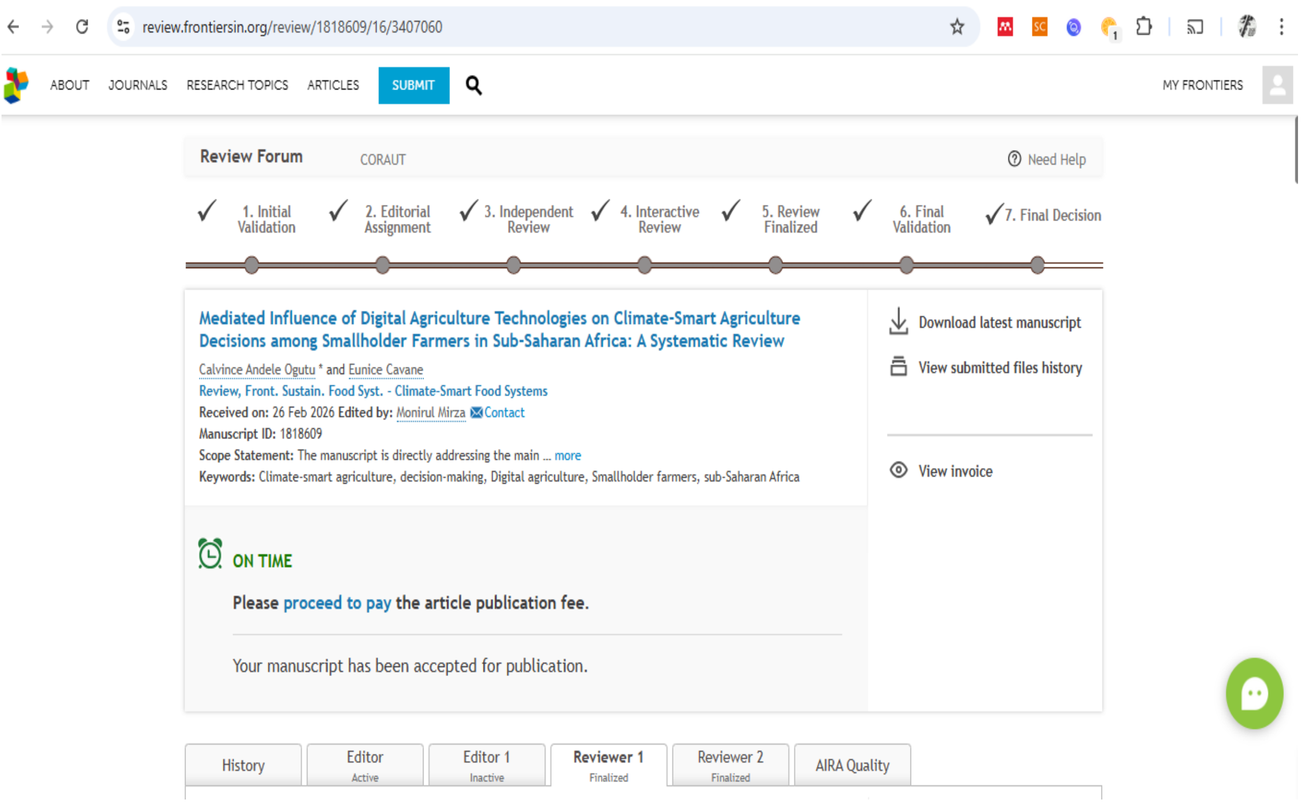
If you have any unresolved queries, please use the chatbot to let us know before your manuscript's publication.

Please fill in this short survey to share your thoughts on your peer review experience. Your feedback helps us improve the process for other authors like you.

What could open science unlock for humanity?
While you're here, watch this video from our CEO and co-founder, Kamila Markram, reflecting on how the global transition to open science is accelerating scientific solutions for healthy lives on a healthy planet.

Thanks for choosing Frontiers. We hope to see you again soon.

Regards,



Mediated Influence of Digital Agriculture Technologies on Climate-Smart Agriculture Decisions among Smallholder Farmers in Sub-Saharan Africa: A Systematic Review

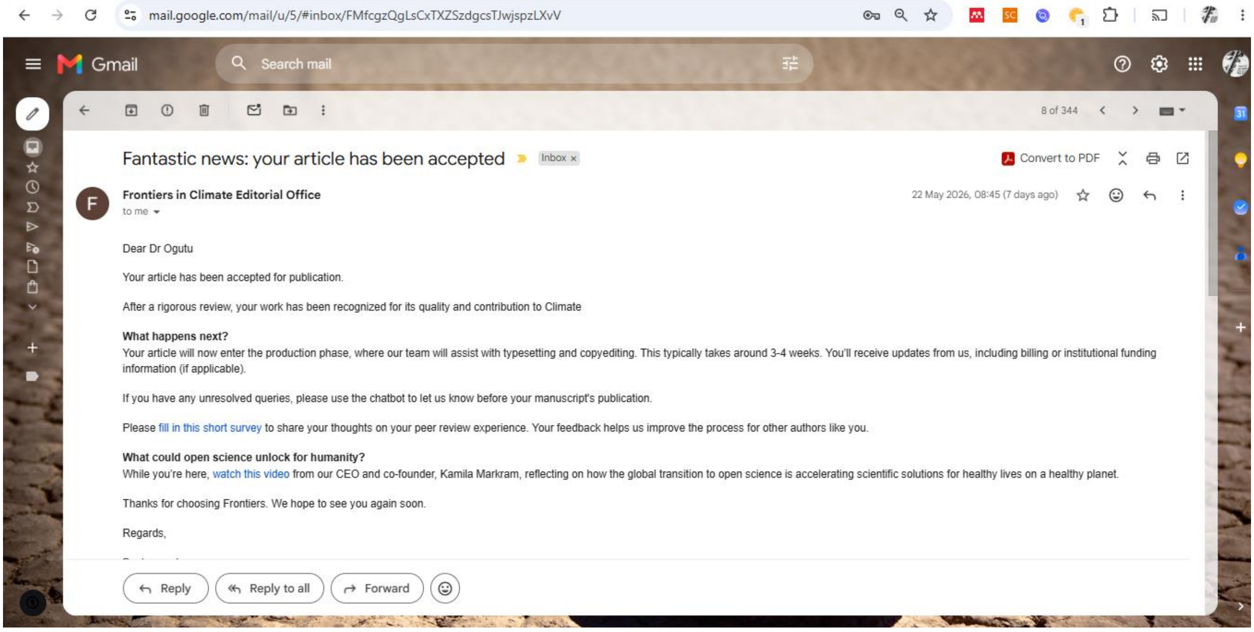
Calvince Andele Ogutu * and Eunice Cavane
Review, Front. Sustain. Food Syst. - Climate-Smart Food Systems
Received on: 26 Feb 2026 **Edited by:** Monirul Mirza ✉Contact
Manuscript ID: 1818609
Scope Statement: The manuscript is directly addressing the main ... more
Keywords: Climate-smart agriculture, decision-making, Digital agriculture, Smallholder farmers, sub-Saharan Africa

ON TIME

Please proceed to pay the article publication fee.

Your manuscript has been accepted for publication.

Appendix 5: Proof of acceptance for Manuscript I publication



Fantastic news: your article has been accepted

Frontiers in Climate Editorial Office
to me

22 May 2026, 08:45 (7 days ago)

Dear Dr Ogutu

Your article has been accepted for publication.

After a rigorous review, your work has been recognized for its quality and contribution to Climate

What happens next?
Your article will now enter the production phase, where our team will assist with typesetting and copyediting. This typically takes around 3-4 weeks. You'll receive updates from us, including billing or institutional funding information (if applicable).

If you have any unresolved queries, please use the chatbot to let us know before your manuscript's publication.

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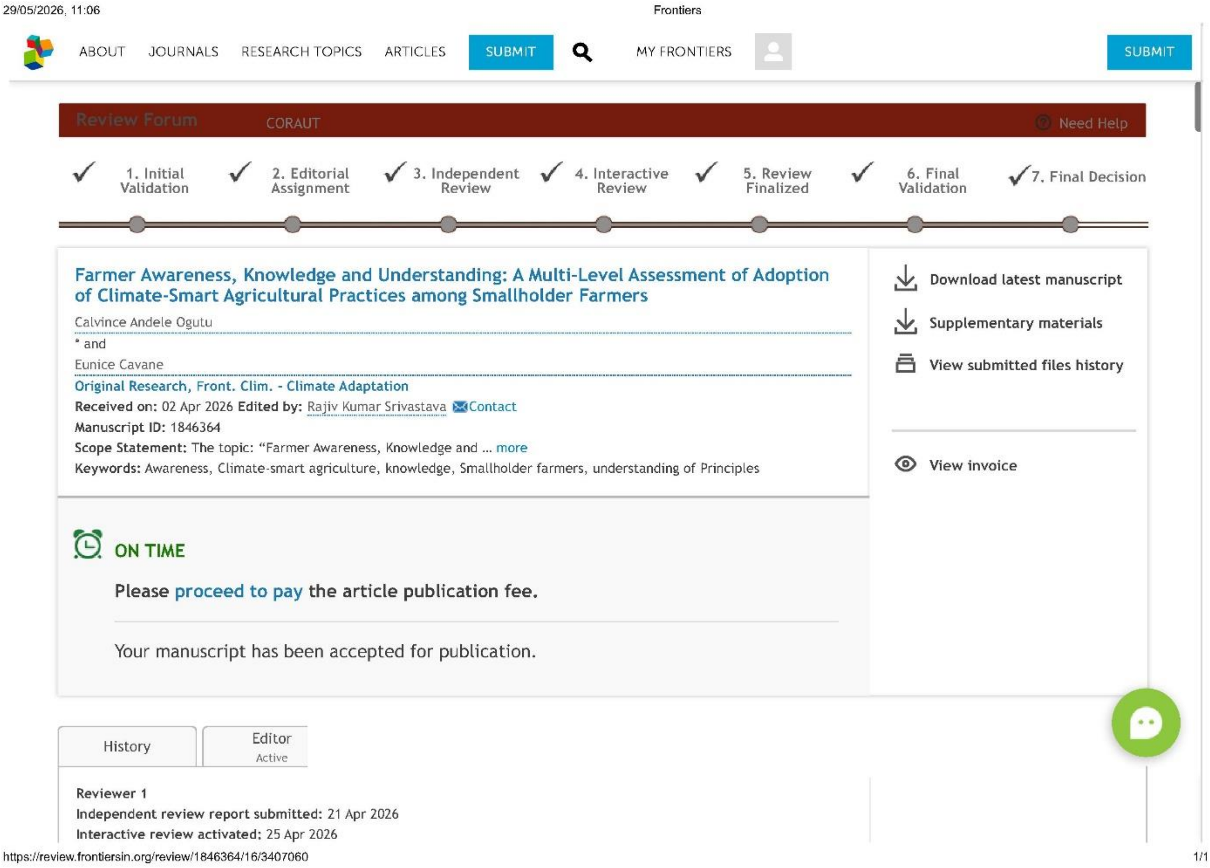

Farmer Awareness, Knowledge and Understanding: A Multi-Level Assessment of Adoption of Climate-Smart Agricultural Practices among Smallholder Farmers

Calvince Andele Ogutu
* and
Eunice Cavane

Original Research, Front. Clim. - Climate Adaptation
Received on: 02 Apr 2026 **Edited by:** Rajiv Kumar Srivastava Contact
Manuscript ID: 1846364
Scope Statement: The topic: "Farmer Awareness, Knowledge and ... more
Keywords: Awareness, Climate-smart agriculture, knowledge, Smallholder farmers, understanding of Principles

ON TIME

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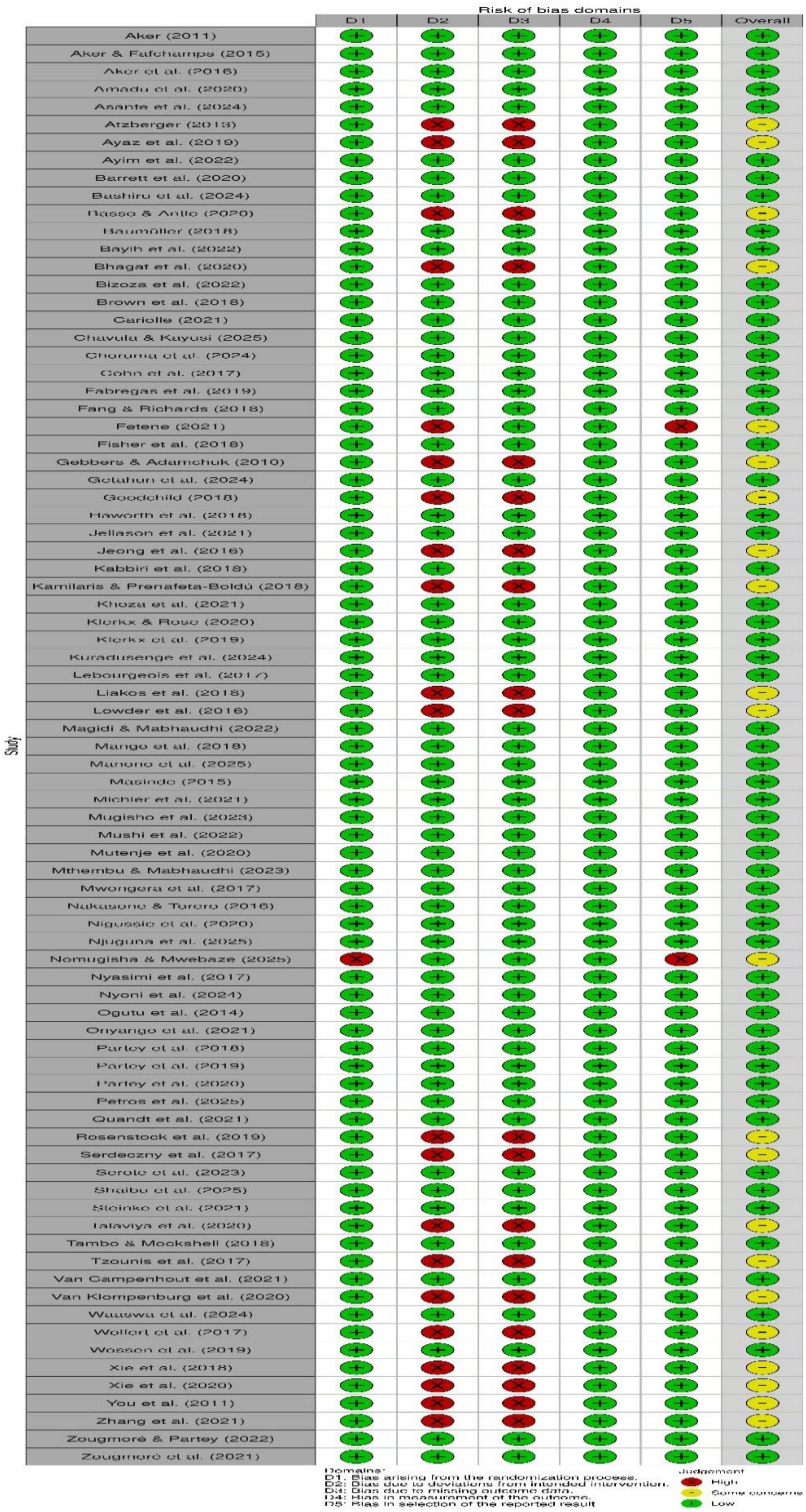
Reviewer 1
Independent review report submitted: 21 Apr 2026
Interactive review activated: 25 Apr 2026

Appendix 6: Detailed risk of bias for included studies (ROBVIS)



Study	D1	D2	D3	D4	D5	Overall
Aker (2011)	+	+	+	+	+	+
Aker & Fafchamps (2015)	+	+	+	+	+	+
Aker et al. (2016)	+	+	+	+	+	+
Amadu et al. (2020)	+	+	+	+	+	+
Asante et al. (2024)	+	+	+	+	+	+
Atzberger (2013)	+	X	X	+	+	−
Ayaz et al. (2019)	+	X	X	+	+	−
Ayim et al. (2022)	+	+	+	+	+	+
Barrett et al. (2020)	+	+	+	+	+	+
Bashiru et al. (2024)	+	+	+	+	+	+
Basso & Antle (2020)	+	X	X	+	+	−
Baumüller (2018)	+	+	+	+	+	+
Bayih et al. (2022)	+	+	+	+	+	+
Bhagat et al. (2020)	+	X	X	+	+	−
Bizoza et al. (2022)	+	+	+	+	+	+
Brown et al. (2018)	+	+	+	+	+	+
Cariolle (2021)	+	+	+	+	+	+
Chavula & Kayusi (2025)	+	+	+	+	+	+
Choruma et al. (2024)	+	+	+	+	+	+
Cohn et al. (2017)	+	+	+	+	+	+
Fabregas et al. (2019)	+	+	+	+	+	+
Fang & Richards (2018)	+	+	+	+	+	+
Fetene (2021)	+	X	+	+	X	−
Fisher et al. (2018)	+	+	+	+	+	+
Gebbers & Adamchuk (2010)	+	X	X	+	+	−
Getahun et al. (2024)	+	+	+	+	+	+
Goodchild (2018)	+	X	X	+	+	−
Haworth et al. (2018)	+	+	+	+	+	+
Jellason et al. (2021)	+	+	+	+	+	+
Jeong et al. (2016)	+	X	X	+	+	−
Kabbiri et al. (2018)	+	+	+	+	+	+
Kamilaris & Prenafeta-Boldú (2018)	+	X	X	+	+	−
Khoza et al. (2021)	+	+	+	+	+	+
Klerkx & Rose (2020)	+	+	+	+	+	+
Klerkx et al. (2019)	+	+	+	+	+	+
Kuradusenge et al. (2024)	+	+	+	+	+	+
Lebourgeois et al. (2017)	+	+	+	+	+	+
Liakos et al. (2018)	+	X	X	+	+	−
Lowder et al. (2016)	+	X	X	+	+	−
Magidi & Mabhaudhi (2022)	+	+	+	+	+	+
Mango et al. (2018)	+	+	+	+	+	+
Manono et al. (2025)	+	+	+	+	+	+
Masinde (2015)	+	+	+	+	+	+
Michler et al. (2021)	+	+	+	+	+	+
Mugisho et al. (2023)	+	+	+	+	+	+
Mushi et al. (2022)	+	+	+	+	+	+
Mutenje et al. (2020)	+	+	+	+	+	+
Mthembu & Mabhaudhi (2023)	+	+	+	+	+	+
Mwongera et al. (2017)	+	+	+	+	+	+
Nakasone & Torero (2016)	+	+	+	+	+	+
Nigussie et al. (2020)	+	+	+	+	+	+
Njuguna et al. (2025)	+	+	+	+	+	+
Nomugisha & Mwebaze (2025)	X	+	+	+	X	−
Nyasimi et al. (2017)	+	+	+	+	+	+
Nyoni et al. (2024)	+	+	+	+	+	+
Ogutu et al. (2014)	+	+	+	+	+	+
Onyango et al. (2021)	+	+	+	+	+	+
Partey et al. (2018)	+	+	+	+	+	+
Partey et al. (2019)	+	+	+	+	+	+
Partey et al. (2020)	+	+	+	+	+	+
Petros et al. (2025)	+	+	+	+	+	+
Quandt et al. (2021)	+	+	+	+	+	+
Rosenstock et al. (2019)	+	X	X	+	+	−
Serdeczny et al. (2017)	+	X	X	+	+	−
Serote et al. (2023)	+	+	+	+	+	+
Shaibu et al. (2025)	+	+	+	+	+	+
Steinke et al. (2021)	+	+	+	+	+	+
Talaviya et al. (2020)	+	X	X	+	+	−
Tambo & Mockshell (2018)	+	+	+	+	+	+
Tzounis et al. (2017)	+	X	X	+	+	−
Van Campenhout et al. (2021)	+	+	+	+	+	+
Van Klompenburg et al. (2020)	+	X	X	+	+	−
Waaswa et al. (2024)	+	+	+	+	+	+
Wolfert et al. (2017)	+	X	X	+	+	−
Wossen et al. (2019)	+	+	+	+	+	+
Xie et al. (2018)	+	X	X	+	+	−
Xie et al. (2020)	+	X	X	+	+	−
You et al. (2011)	+	X	X	+	+	−
Zhang et al. (2021)	+	X	X	+	+	−
Zougmoré & Partey (2022)	+	+	+	+	+	+
Zougmoré et al. (2021)	+	+	+	+	+	+

Domains:
D1: Bias arising from the randomization process.
D2: Bias due to deviations from intended intervention.
D3: Bias due to missing outcome data.
D4: Bias in measurement of the outcome.
D5: Bias in selection of the reported result.

Judgement
X High
− Some concerns
+ Low