AI-DRIVEN STAKEHOLDER MANAGEMENT STRATEGIES AND PROJECT SUSTAINABILITY IN AGRICULTURE AND FOOD SECURITY PROJECTS, KENYAN CONTEXT

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ABSTRACT

Agriculture and food security projects in Kenya continue to face sustainability challenges associated with fragmented stakeholder coordination, planning inefficiencies and suboptimal resource allocation. Although artificial intelligence (AI) is increasingly recognised as a potential enabler of data-driven project management, its application to stakeholder management and agricultural project sustainability in Kenya remains insufficiently institutionalised. This study examined the effects of four AI-driven stakeholder management strategies; machine learning, AI-based communication, AI mapping tools, and AI-driven monitoring and evaluation (M&E) on the sustainability of agriculture and food security projects in Kenya. A convergent parallel mixed-methods design was employed. Quantitative data were collected from 138 participants through stratified random sampling across key departments of the Agriculture and Food Authority (AFA), while qualitative evidence was obtained through semi-structured interviews with project and policy experts. Quantitative analysis using SPSS Version 23 indicated a strong joint relationship between the four AI dimensions and project sustainability ($R = .826$, $R^2 = .682$, $F(4, 98) = 52.59$, $p < .001$). AI-driven M&E ($\beta = .389$, $p < .001$) and machine learning ($\beta = .322$, $p < .001$) were the strongest reported predictors. Thematic analysis using NVivo 14 reinforced the quantitative findings through the themes of AI-enabled stakeholder visibility and real-time monitoring for sustainability decision-making. The findings indicate that AI can strengthen stakeholder coordination, resource-related decision-making, communication and monitoring within agricultural projects. The study contributes empirical evidence on AI-driven stakeholder management in the Kenyan agricultural context and supports greater institutionalisation of AI systems, staff capacity development and operational procedures for sustainable project delivery.

Keywords: Artificial Intelligence, Stakeholder Management, Machine Learning, AI Communication, AI Mapping, Monitoring and Evaluation, Project Sustainability, Agriculture, Kenya

INTRODUCTION

Background to the Study

Agriculture and food security projects operate within increasingly complex economic, environmental and social conditions in which effective stakeholder coordination and adaptive resource management are central to sustainable outcomes. Globally, artificial intelligence (AI) has emerged as a data-driven technology capable of supporting decision-making, resource optimisation, forecasting and project management processes. Its relevance to sustainability arises from its ability to process large volumes of information and support more timely responses to changing project conditions (Challoumis, 2024; Shang et al., 2023; Martínez-Peláez et al., 2023). In agricultural settings, these capabilities are particularly relevant because project performance depends on the interaction of farmers, communities, government agencies, development partners, regulators and other actors whose interests and decisions affect implementation and long-term outcomes (Freeman, 1984; Adebayo et al., 2024; Ozor et al., 2024).

The sustainability of agricultural and food security projects nevertheless remains difficult to achieve because economic viability, social inclusion and environmental protection must be pursued simultaneously. Existing evidence indicates that digital technologies can strengthen resource allocation, improve decision support and enhance stakeholder coordination, while AI-enabled applications can provide predictive and real-time information for project decision-making (Bachmann et al., 2022; Kar et al., 2022; Pigola et al., 2021). In project environments characterised by resource constraints and uncertainty, the capacity to identify emerging risks, monitor implementation and communicate with stakeholders can therefore influence the continuity and sustainability of project interventions (Shang et al., 2023; Zadeh et al., 2024; Turyasingura et al., 2024).

These challenges are particularly significant in Sub-Saharan Africa, where agricultural systems continue to face food insecurity, climate pressures, institutional constraints and limitations in technological capacity. Research on African agricultural development indicates that AI has potential to improve agricultural decision-making, resource management and food-system resilience, but implementation remains constrained by infrastructure deficits, limited digital capacity and institutional barriers (Chukwuma et al., 2024; Aderibigbe et al., 2023; Ozor et al., 2024). The benefits of AI therefore cannot be considered independently of stakeholder engagement and organisational readiness because technology must operate within institutional and social environments that determine whether information is understood, accepted and translated into project decisions (Moinuddin et al., 2024; Adebayo et al., 2024; Wakunuma et al., 2020).

Within this regional context, the application of AI to stakeholder management provides an opportunity to move agricultural projects from predominantly periodic and manual engagement toward more continuous, data-informed interaction. Machine learning can support forecasting and

resource allocation; AI-based communication can facilitate timely information exchange; mapping technologies can improve understanding of spatial and environmental conditions; and AI-enabled monitoring and evaluation can strengthen real-time tracking of project performance (Kaur et al., 2024; Tandon & Shaheen, 2024; Sarku et al., 2023). Such applications are relevant to the economic, social and environmental dimensions of project sustainability identified within the Triple Bottom Line perspective (Elkington, 1997; Mubangizi, 2024; Chisika et al., 2023).

Kenya provides an important setting for examining these relationships because agriculture remains a major contributor to livelihoods and national economic activity. The sector contributes approximately 23% of gross domestic product and engages about 40% of the population, making the performance and sustainability of agricultural initiatives important to wider development outcomes (Ozor et al., 2024). At the project level, however, sustainability has been associated with challenges including financing constraints, governance weaknesses, resource inefficiencies, climate variability and inadequate stakeholder coordination (Lekesanyal, 2021; Chisika et al., 2023; Turyasingura et al., 2024). These conditions create a practical need for approaches capable of improving coordination, information management, resource utilisation and project monitoring. The Agriculture and Food Authority (AFA) provides a particularly relevant institutional setting because its responsibilities intersect with agricultural development, food systems and stakeholder coordination. Existing Kenyan evidence has identified stakeholder engagement and operational efficiency as important considerations in agricultural and food-security initiatives, while emerging research points to AI as a potential mechanism for improving decision-making and resource management (Chepleting et al., 2023; Aderibigbe & Oyebode, 2023; Gideon, 2024). Nevertheless, the incorporation of AI into stakeholder management processes remains relatively underdeveloped, particularly when considered through the distinct dimensions of machine learning, AI-based communication, AI mapping, and AI-driven monitoring and evaluation (Moinuddin et al., 2024; Gikunda, 2024; Aderibigbe et al., 2023).

The sustainability challenge is therefore not simply whether AI is available, but whether AI-enabled stakeholder management strategies are associated with measurable improvements in project sustainability. Stakeholder management requires the identification, coordination and engagement of actors whose interests influence project outcomes, while sustainability requires attention to economic, social and environmental consequences over time (Freeman, 1984; Elkington, 1997; Mitchell et al., 1997). AI potentially strengthens this relationship by providing project actors with improved information, predictive capabilities and monitoring mechanisms; however, evidence from resource-constrained settings suggests that infrastructure, skills, institutional capacity and implementation conditions remain important constraints (Adebayo et al., 2024; Moinuddin et al., 2024; Turyasingura et al., 2024).

Against this background, the present study examined whether AI-driven stakeholder management strategies were associated with project sustainability in agriculture and food security projects in

Kenya. Rather than treating AI as a single technological construct, the study examined four specific dimensions: machine learning, AI-based communication, AI mapping tools, and AI-driven monitoring and evaluation. This dimensional approach enabled the study to connect particular AI applications with distinct sustainability concerns while retaining project sustainability as the overarching outcome (Shang et al., 2023; Martínez-Peláez et al., 2023; Chukwuma et al., 2024).

Novelty

The novelty of the study lies in its integration of AI-driven stakeholder management with project sustainability within the Kenyan agriculture and food-security context. Although previous studies have examined AI, digital transformation and sustainable development, comparatively limited attention has been directed toward the specific role of AI-enabled stakeholder management in agricultural projects in Kenya (Martínez-Peláez et al., 2023; Gikunda, 2024; Ozor et al., 2024). The study therefore moved beyond viewing AI primarily as a production or agricultural technology and examined its application to stakeholder-oriented project management processes.

A second element of novelty concerned the differentiation of AI-driven stakeholder management into four operational dimensions. Machine learning was considered in relation to data-driven forecasting, resource allocation and economic sustainability; AI-based communication was examined in relation to stakeholder interaction and social sustainability; AI mapping tools were linked to environmental information and management; and AI-driven M&E was considered in relation to broader project sustainability (Kaur et al., 2024; Moinuddin et al., 2024; Tandon & Shaheen, 2024). This operationalisation provided a more specific empirical basis for examining how AI applications may contribute to sustainability rather than treating technological adoption as a homogeneous construct.

The study also extends the emerging discussion on responsible and context-sensitive AI adoption in developing economies. Previous research has identified substantial opportunities associated with AI while simultaneously reporting infrastructure, skills, institutional and ethical barriers to implementation (Aderibigbe et al., 2023; Jobin et al., 2019; Stahl & Wright, 2018). By examining AI within actual agricultural project-management processes in Kenya, the study contributes context-specific empirical evidence on the relationship between technological capabilities, stakeholder management and sustainability outcomes.

Problem Statement

Despite the strategic importance of agriculture to Kenya's economy and food security, agricultural and food-security projects continue to experience sustainability challenges associated with financial constraints, governance weaknesses, climate variability, inefficient resource utilisation and limited stakeholder engagement (Lekesanyal, 2021; Ozor et al., 2024; Turyasingura et al., 2024). These challenges can weaken project continuity and limit the capacity of interventions to

generate sustained economic, social and environmental benefits. Existing evidence also indicates a persistent gap between sustainability frameworks and their practical implementation in resource-constrained agricultural settings (Chisika et al., 2023; Gryshova et al., 2024; Turyasingura et al., 2024).

At the same time, AI is increasingly identified as a potential mechanism for improving decision-making, resource management, communication and monitoring in agricultural systems. However, evidence from Kenya and other developing-country contexts suggests that AI adoption remains constrained by technological infrastructure, digital skills, organisational readiness and policy limitations (Aderibigbe et al., 2023; Moinuddin et al., 2024; Gikunda, 2024). Consequently, there remains insufficient empirical evidence demonstrating whether and to what extent specific AI-driven stakeholder management strategies contribute to sustainability in agricultural and food-security projects.

The central empirical problem addressed by this study was therefore the limited context-specific evidence connecting AI-driven stakeholder management strategies with project sustainability in Kenya. Existing literature has established the potential of AI for agricultural decision-making and sustainability, but relatively less is known about the direct contribution of machine learning, AI-based communication, AI mapping tools, and AI-driven M&E within agricultural project-management environments (Shang et al., 2023; Chukwuma et al., 2024; Sarku et al., 2023). The study consequently examined these four direct relationships without introducing mediating or moderating variables.

Object of the Study

The object of the study was AI-driven stakeholder management strategies and their contribution to the sustainability of agriculture and food-security projects in Kenya.

Aim of the study

The study aimed to examine how AI-driven stakeholder management strategies contributed to the economic, social and environmental sustainability of agriculture and food-security projects in Kenya.

Specific Objectives

The study sought to examine the effect of machine learning on the economic sustainability of agriculture and food-security projects in Kenya; assess the role of AI-based communication in enhancing the social sustainability of agriculture and food-security projects; investigate the impact of AI mapping tools on environmental sustainability; and examine the influence of AI-driven monitoring and evaluation on the overall sustainability of agriculture and food-security projects in Kenya.

Research Objectives and Hypotheses

The study tested four null hypotheses corresponding directly to the four dimensions of AI-driven stakeholder management. H_{01} stated that machine learning did not have a significant effect on the economic sustainability of agriculture and food-security projects in Kenya. H_{02} stated that AI-based communication did not significantly enhance social sustainability. H_{03} stated that AI mapping tools did not have a significant impact on environmental sustainability. H_{04} stated that AI-driven monitoring and evaluation did not significantly improve the overall sustainability of agriculture and food-security projects in Kenya. The hypotheses established a direct empirical structure linking each AI dimension to its specified sustainability outcome.

Research Methods

The study adopted a convergent parallel mixed-methods design to obtain complementary quantitative and qualitative evidence concerning AI-driven stakeholder management and project sustainability. The mixed-methods approach was appropriate because the research examined measurable relationships while also requiring contextual understanding of how AI technologies were experienced and applied within agricultural project environments (Creswell & Creswell, 2018; Creswell & Plano Clark, 2023; Hirose & Creswell, 2023). Quantitative data were collected from 138 participants through stratified random sampling across key AFA departments, while qualitative evidence was obtained through semi-structured interviews with project and policy experts.

The quantitative component provided the basis for testing the four direct relationships specified in the study. Survey research enabled systematic measurement of AI utilisation, stakeholder-management practices and sustainability-related outcomes, while statistical analysis provided evidence concerning the strength and significance of the relationships (Creswell & Creswell, 2018; Fellows & Liu, 2021; Oranga, 2025). The qualitative component complemented these findings by examining stakeholder experiences and institutional conditions surrounding AI use, thereby providing contextual interpretation of the quantitative results (John et al., 2023; ManjulaSelvam et al., 2023; Hirose & Creswell, 2023).

Quantitative data were analysed using SPSS Version 23, while qualitative data were subjected to thematic analysis using NVivo 14. The quantitative model examined the joint contribution of the four AI dimensions to project sustainability, while the qualitative analysis identified themes relevant to stakeholder visibility, monitoring and sustainability decision-making. The integration of quantitative and qualitative evidence strengthened interpretation through methodological triangulation and provided a more comprehensive account of AI-driven stakeholder management in the study setting (Creswell & Plano Clark, 2023; Hirose & Creswell, 2023; DePoy, 2024).
The study was also informed by established ethical principles concerning research participation, responsible data use and AI-related ethical considerations. Ethical concerns surrounding transparency, privacy, accountability and responsible technological application are particularly

relevant where AI systems process stakeholder information and influence organisational decisions (National Commission, 1979; Jobin et al., 2019; Stahl & Wright, 2018). These considerations were incorporated into the research process to support responsible investigation of AI-enabled project-management practices.

Part I: Theoretical And Empirical Aspects Of Ai-Driven Stakeholder Management Strategies

Conceptual and Theoretical Foundations

AI-driven stakeholder management represents an emerging intersection between stakeholder theory, digital transformation and sustainable project management. Stakeholder management traditionally involves identifying, analysing, engaging and coordinating actors who affect or are affected by project outcomes (Freeman, 1984; Mitchell et al., 1997). In agriculture and food-security projects, these actors include farmers, communities, regulators, project managers, development partners, suppliers and policy actors whose interests and decisions influence project performance. The emergence of artificial intelligence has shifted this process from predominantly periodic and manually mediated engagement toward data-driven, predictive and increasingly real-time interaction. AI can process large volumes of stakeholder and operational information, identify patterns, support forecasting and facilitate faster decision-making, thereby strengthening coordination and responsiveness (Shang et al., 2023; Martínez-Peláez et al., 2023; Adebayo et al., 2024).

The relevance of AI becomes particularly important where agricultural projects operate under resource constraints, environmental uncertainty and fragmented stakeholder interests. AI-enabled analytics can support resource optimisation, risk identification, communication and continuous monitoring, while digital technologies can strengthen the capacity of project actors to respond to changing operational conditions (Challoumis, 2024; Moinuddin et al., 2024; Pigola et al., 2021). However, the literature also indicates that technological capability alone does not guarantee sustainable outcomes. Infrastructure limitations, digital skills, institutional readiness and contextual conditions can constrain implementation, particularly in developing economies (Aderibigbe et al., 2023; Moinuddin et al., 2024; Gikunda, 2024). Consequently, the value of AI-driven stakeholder management is best understood as a direct project-management capability whose contribution depends on how effectively information, stakeholders and project decisions are connected.

The theoretical foundation integrates the Triple Bottom Line (TBL) theory**,** Stakeholder Theory and the Technology Acceptance Model (TAM)**.** TBL conceptualises sustainability through economic, social and environmental outcomes (Elkington, 1997), providing the basis for examining project sustainability beyond financial performance. This is particularly relevant in agriculture, where project viability depends simultaneously on resource efficiency, community benefits and environmental protection (Chisika et al., 2023; Turyasingura et al., 2024; Mubangizi,

2024). Stakeholder Theory complements TBL by explaining why the interests, participation and relationships of project actors matter for sustainable outcomes (Freeman, 1984; Mitchell et al., 1997; Adebayo et al., 2024). TAM provides a technology-oriented perspective by explaining how perceived usefulness and ease of use shape technology acceptance (Davis, 1989), although its explanatory capacity is constrained where infrastructure, organisational support and digital capacity are significant barriers (Moinuddin et al., 2024; Aderibigbe et al., 2023; Shang et al., 2023).

The three theories therefore provide complementary rather than competing explanations. TBL establishes what sustainability means, Stakeholder Theory explains whose interests and relationships must be managed, while TAM explains how users may accept and utilise technological tools. Their integration is particularly appropriate for the present study because AI-driven stakeholder management sits at the intersection of technology, stakeholder coordination and multidimensional sustainability. Nevertheless, the theories were not treated as evidence of causality; rather, they provided the analytical foundation for testing the direct relationships between machine learning, AI-based communication, AI mapping tools, AI-driven monitoring and evaluation, and project sustainability (Elkington, 1997; Freeman, 1984; Davis, 1989).

Theoretical Recheck and Synthesis

A theoretical recheck demonstrates that each framework addresses a different dimension of the study. TBL provides the sustainability outcome against which AI-enabled project practices can be assessed, while Stakeholder Theory explains the importance of information exchange, coordination and responsiveness among project actors. TAM adds an adoption perspective by recognising that the effectiveness of AI depends partly on whether users perceive the technology as useful and manageable. Evidence from African agricultural contexts reinforces the importance of combining technological capability with institutional and stakeholder considerations because infrastructure and capacity constraints may limit AI implementation even where its potential benefits are substantial (Aderibigbe et al., 2023; Adebayo et al., 2024; Moinuddin et al., 2024).

The synthesis also identifies a theoretical gap. Existing sustainability theories were largely developed before contemporary AI applications became prominent and therefore do not explicitly explain machine learning, AI-enabled communication, mapping technologies or intelligent monitoring as stakeholder-management mechanisms. Similarly, Stakeholder Theory establishes the importance of stakeholder relationships but does not specify how algorithmic and data-driven systems may transform those relationships, while TAM concentrates on technology acceptance rather than sustainability outcomes (Freeman, 1984; Davis, 1989; Gikunda, 2024). The present study consequently positions AI as a technological capability operating within stakeholder-management processes and assesses its direct contribution to project sustainability in the Kenyan agricultural context.

Empirical Literature

Machine Learning and Project Sustainability

Machine learning provides a principal mechanism through which AI converts historical and real-time data into predictions, classifications and recommendations. In project environments, this capability can support forecasting, risk identification, resource allocation and decision-making, potentially improving economic sustainability through reduced waste and more efficient utilisation of scarce resources (Aderibigbe & Oyebode, 2023; Kaur et al., 2024; Shang et al., 2023). In agriculture, these applications are particularly relevant because project outcomes are affected by climatic variability, production conditions, supply-chain disruptions and changing stakeholder needs. Machine learning therefore provides a basis for moving stakeholder management from reactive responses toward anticipatory decision-making.

Empirical studies outside agriculture provide evidence supporting this potential while simultaneously revealing an important contextual gap. Cioffi et al. (2020) demonstrated the contribution of AI and machine learning to efficiency and resource optimisation in smart production, while Kovacova and Lăzăroiu (2021) associated deep-learning applications with improved planning and organisational performance. Woschank et al. (2020) similarly showed the relevance of AI to logistics and supply-chain efficiency, whereas Meharie et al. (2022) demonstrated the usefulness of machine-learning algorithms for project cost prediction. Collectively, these studies establish the operational value of machine learning but are predominantly situated in industrial, logistics, energy or construction environments rather than Kenyan agricultural and food-security projects.

Evidence from energy and development studies further demonstrates the broader sustainability relevance of machine learning. Rangel-Martinez et al. (2021) identified opportunities for machine learning to improve energy-system efficiency, while Alova et al. (2021) and Magazzino et al. (2021) demonstrated the value of AI-based prediction and analysis in African energy and economic-development contexts. Mwitondi et al. (2020) also showed how machine learning can support segmentation and analysis of Sustainable Development Goal data. These findings are transferable at the conceptual level to agricultural resource planning, but their sectoral and contextual differences limit direct inference about agricultural project sustainability in Kenya. The present study consequently addressed the empirical gap by testing whether machine learning was associated with sustainability outcomes within agriculture and food-security projects.

AI-Based Communication and Project Sustainability

AI-based communication extends stakeholder management through automated information exchange, intelligent feedback, virtual assistants, chatbots and data-supported communication channels. Its relevance to sustainability arises from the possibility of reducing information delays, improving responsiveness and increasing the accessibility of project information to heterogeneous stakeholders (Adebayo et al., 2024; Moinuddin et al., 2024; Zadeh et al., 2024). In agricultural

projects, where stakeholders may be geographically dispersed and differ in technical knowledge and institutional influence, timely communication can strengthen coordination, participation and social sustainability. AI-based communication therefore represents not simply a technological communication channel but a mechanism for improving the flow of information within stakeholder relationships.

Evidence from other project environments supports this proposition. Wamba-Taguimdje et al. (2020) found that AI-supported organisational transformation could improve communication and decision-making, while Jallow et al. (2023) identified positive implications of AI-enabled communication for project coordination in construction. Waqar et al. (2023) similarly demonstrated the potential of AI-supported drones to improve information and project-management processes. Verdecchia et al. (2022) further linked data-centric AI with sustainability-oriented communication and decision-making. However, these studies largely examined construction, organisational transformation or broader technological contexts, leaving limited empirical evidence regarding AI-based communication within Kenyan agricultural and food-security projects.

The Kenyan literature provides contextual evidence but remains fragmented. Kioko (2022) identified infrastructural and skills-related considerations surrounding AI adoption in Kenyan media, while Gideon (2024) reported the relevance of AI to communication and coordination in Kenya's agri-food supply chain. Muya (2024) similarly demonstrated emerging AI applications in Kenyan communication environments. These studies suggest that the technological foundations for AI-supported communication are developing, but they do not directly establish its relationship with social sustainability in agricultural projects. This gap justified the study's second empirical focus: determining whether AI-based communication contributed to social sustainability through improved stakeholder participation, information exchange and coordination (Gideon, 2024; Moinuddin et al., 2024; Adebayo et al., 2024).

AI Mapping Tools and Environmental Sustainability

AI mapping tools combine geospatial information, remote sensing, satellite data and analytical algorithms to generate spatially explicit information for project decisions. In agricultural settings, these tools can support land-use planning, resource identification, environmental monitoring and risk profiling. Their sustainability relevance lies in their capacity to improve the precision with which land, water and other natural resources are managed while simultaneously providing a common evidence base for stakeholders (Martínez-Peláez et al., 2023; Tandon & Shaheen, 2024; Ali et al., 2024). Such capabilities are particularly important where environmental conditions vary spatially and where conventional monitoring may be costly or infrequent.

The empirical literature demonstrates this potential across related sectors. Kar et al. (2022), through a systematic review, identified AI as a significant enabler of resource optimisation and

sustainability, although their analysis was not agriculture-specific. Debrah et al. (2022) demonstrated the environmental optimisation potential of AI in green-building contexts, while Bokhari and Myeong (2022) linked AI-supported data analysis with improved resource-management decisions in smart cities. Chisika and Yeom (2024) further showed how AI could support participatory resource management in forestry. These findings collectively support the proposition that AI mapping can strengthen environmental decision-making, but they also reveal a persistent transferability problem because much of the evidence originates outside agricultural production systems.

The Kenyan context adds further evidence regarding the conditions under which mapping technologies may operate. Oloo (2023) identified infrastructure, technological capacity and risk-related barriers to AI adoption, while Ominde et al. (2023) emphasised stakeholder integration as an important condition for effective project delivery. Chisika et al. (2023) also demonstrated the relevance of AI to sustainable resource management in Kenya, although their focus was forestry rather than agriculture. Thus, the literature supports the technological plausibility of AI mapping while leaving insufficient direct evidence concerning environmental sustainability in Kenyan agriculture and food-security projects. The present study addressed this gap by examining whether AI mapping tools were associated with environmental sustainability outcomes.

AI-Driven Monitoring and Evaluation and Project Sustainability

AI-driven monitoring and evaluation represents a shift from periodic assessment toward continuous, data-supported oversight. Intelligent dashboards, remote monitoring, automated reporting, sensors and anomaly-detection systems can facilitate timely identification of deviations in project performance and resource use. In principle, these capabilities strengthen accountability, transparency and evidence-based decision-making, all of which are important for sustained project performance (Bachmann et al., 2022; John et al., 2023; Zadeh et al., 2024). In agricultural projects, real-time monitoring may be particularly valuable because environmental and production conditions can change rapidly, making delayed evaluation less useful for corrective action.

Empirical evidence from related sectors supports the relevance of intelligent monitoring. Bachmann et al. (2022) established the contribution of data-driven technologies to Sustainable Development Goal implementation, while John et al. (2023) showed how AI-driven business processes can improve operational monitoring and decision-making. Studies in construction also reported improvements in resource allocation and efficiency through AI-supported monitoring and simulation (Adewale et al., 2024; Scott & Bommu, 2024). Ziemba et al. (2024) similarly identified broad potential for AI to strengthen SDG-related monitoring and environmental resource management. Nevertheless, most of this evidence is general or sector-specific outside agriculture, making direct conclusions about Kenyan agricultural projects premature.

Kenyan evidence has begun to narrow this gap. Gideon (2024) identified AI applications in Kenya's agri-food supply chain for coordination, monitoring and decision-making, while related studies demonstrate the potential of AI for sustainable resource management (Chisika et al., 2023; Gikunda, 2024). However, the existing evidence has not sufficiently examined AI-driven

monitoring and evaluation as a stakeholder-management strategy across the broader agricultural project cycle. The present study therefore tested its direct relationship with project sustainability, with particular attention to the economic, social and environmental dimensions represented in the TBL framework (Elkington, 1997; Bachmann et al., 2022; Gideon, 2024).

Composite Empirical Index

The reviewed evidence can be consolidated into the following index.

Table 1. Composite empirical index of AI-driven stakeholder management and project sustainability

AI-driven strategy	Main sustainability pathway	Evidence from literature	Principal empirical gap addressed
Machine learning	Forecasting, cost/resource optimisation and economic efficiency	Cioffi et al. (2020); Rangel-Martinez et al. (2021); Meharie et al. (2022)	Limited direct evidence in Kenyan agricultural projects
AI-based communication	Information access, participation, coordination and social sustainability	Wamba-Taguimdje et al. (2020); Jallow et al. (2023); Gideon (2024)	Limited agriculture-specific evidence on social sustainability
AI mapping tools	Land, water, spatial-risk and environmental-resource management	Kar et al. (2022); Debrah et al. (2022); Chisika & Yeom (2024)	Limited direct evidence in Kenyan agriculture
AI-driven M&E	Continuous monitoring, accountability, reporting and corrective decision-making	Bachmann et al. (2022); John et al. (2023); Ziemba et al. (2024)	Limited evidence across the agricultural project cycle in Kenya
Integrated AI stakeholder management	Economic, social and environmental project sustainability	Shang et al. (2023); Martínez-Peláez et al. (2023); Adebayo et al. (2024)	Insufficient empirical evidence testing the four strategies jointly in the Kenyan context

Source: Synthesised from the empirical literature reviewed by the researcher.

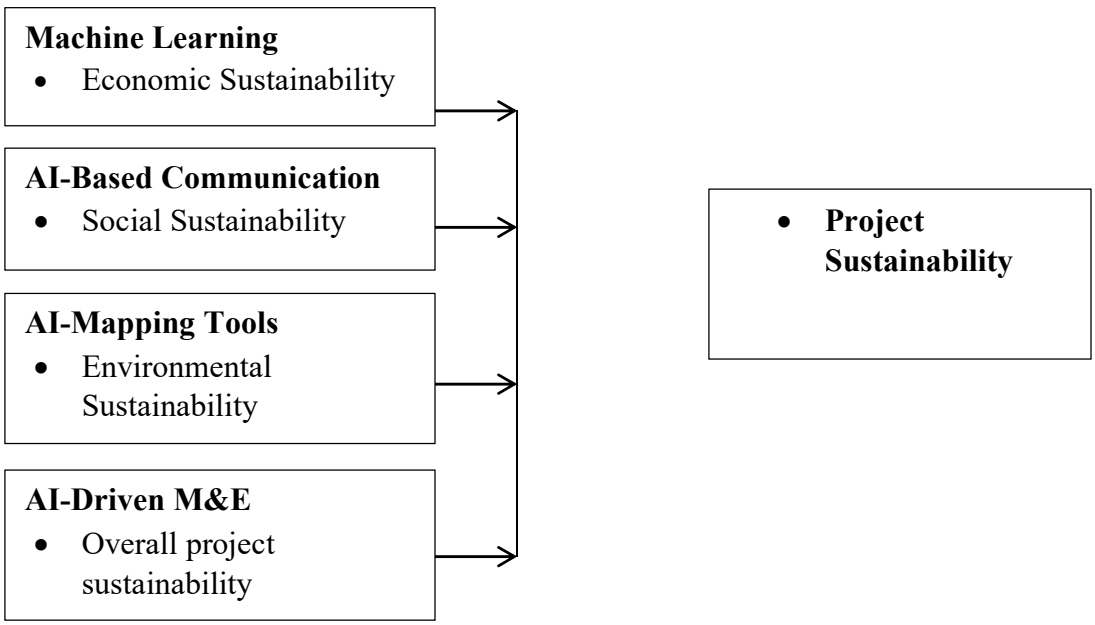
The composite index indicates a consistent pattern across the literature: AI applications are associated with improved prediction, communication, resource management and monitoring, yet the evidence is fragmented across sectors and geographical settings. Studies have frequently examined AI in construction, energy, manufacturing, logistics, forestry, media or general

sustainability rather than directly testing agriculture and food-security projects in Kenya (Cioffi et al., 2020; Woschank et al., 2020; Kar et al., 2022). Even where Kenyan evidence exists, it has tended to focus on AI adoption, supply chains or natural-resource management rather than the integrated management of agricultural project stakeholders. This fragmentation established the empirical rationale for examining the four AI strategies within one direct-effects model (Gideon, 2024; Aderibigbe et al., 2023; Chukwuma et al., 2024).

Conceptual Framework

The literature and theoretical synthesis culminated in a parsimonious conceptual framework in which the four AI-driven stakeholder-management strategies were specified as direct predictors of project sustainability. Machine learning was linked principally to economic sustainability through forecasting, resource optimisation and efficiency; AI-based communication to social sustainability through participation, information sharing and stakeholder responsiveness; AI mapping tools to environmental sustainability through spatial planning and resource monitoring; and AI-driven monitoring and evaluation to overall project sustainability through continuous oversight, accountability and evidence-based decision-making (Elkington, 1997; Freeman, 1984; Shang et al., 2023).

Figure 1. Conceptual Framework of AI-Driven Stakeholder Management and Project Sustainability



Sources: Researcher, 2025

The framework examined the direct contribution of AI-driven stakeholder-management strategies to project sustainability. This specification was consistent with the study objectives and hypotheses and enabled the empirical analysis to determine both the individual and collective contribution of machine learning, AI-based communication, AI mapping tools, and AI-driven monitoring and

evaluation (Shang et al., 2023; Martínez-Peláez et al., 2023; Zadeh et al., 2024). The framework consequently translated the theoretical propositions into an empirically testable structure suited to the Kenyan agriculture and food-security project context.

METHODOLOGICAL ASPECTS OF AI-DRIVEN STAKEHOLDER MANAGEMENT STRATEGIES

Research Design, Philosophy and Study Context

The study employed a convergent parallel mixed-methods design, combining quantitative and qualitative evidence to examine the relationship between AI-driven stakeholder-management strategies and project sustainability. The design was appropriate because the study required both measurable evidence of relationships among the variables and contextual explanations of how AI was experienced and applied within agricultural project environments. Mixed-methods research enables numerical patterns to be considered alongside qualitative interpretations, thereby strengthening the breadth and depth of evidence available for complex project-management phenomena (Creswell & Creswell, 2018; Creswell & Plano Clark, 2023; Hirose & Creswell, 2023). The approach was also consistent with pragmatism, which accommodates methodological pluralism where different forms of evidence contribute to answering an empirical research problem (DePoy, 2024; Fellows & Liu, 2021; Oranga, 2025).

The empirical setting was the Agriculture and Food Authority (AFA), whose institutional mandate places it within the governance and operational environment of Kenya's agricultural and food-security system. The study targeted personnel involved in strategic and operational management, project management, agricultural operations, policy and strategy, and monitoring and evaluation. This setting was considered appropriate because these functions are directly connected with project planning, implementation, stakeholder coordination and sustainability decisions (Chepleting et al., 2023; Kwamboka & Sang, 2019; Gideon, 2024). The methodological focus was therefore placed on respondents with direct knowledge of agricultural project-management processes rather than attempting to generalise from populations without relevant project experience.

Population, Sampling and Data Collection

The study population comprised 650 personnel, from which a quantitative sample of 138 respondents was obtained using the Taro Yamane approach at a 5% margin of error. Stratification was used to ensure representation across five functional areas: project management, agricultural operations, policy and strategy, monitoring and evaluation, and administration/support. Stratified sampling was appropriate because the functions differ in their exposure to project planning, stakeholder management, technology use and sustainability decisions (Chary, 2024; Kwamboka & Sang, 2019; Ngulube, 2022). The quantitative component therefore provided structured evidence across relevant organisational roles, while the qualitative component provided contextual explanations from project and policy experts.

The data were collected using structured questionnaires supplemented by semi-structured interviews. Questionnaire items captured the four AI-driven stakeholder-management dimensions and indicators of project sustainability, while interviews provided deeper explanations of AI use, stakeholder coordination, monitoring practices and implementation experiences. The instrument was developed from the study constructs and informed by the reviewed literature, with contextual adaptation to the Kenyan agricultural project environment. Combining standardised measurement with qualitative inquiry strengthened triangulation and reduced dependence on a single source of evidence (Creswell & Creswell, 2018; Creswell & Plano Clark, 2023; Hirose & Creswell, 2023).
Instrument quality was assessed through pilot testing, validity procedures and internal-consistency analysis. The pilot process was used to evaluate clarity, relevance and completeness before the main data collection, while reliability was examined using Cronbach's alpha. The reported coefficients were 0.82 for machine learning, 0.79 for AI-based communication, 0.85 for AI mapping tools, 0.81 for monitoring and evaluation, and 0.87 for project sustainability, all exceeding the commonly applied 0.70 threshold. These results indicated satisfactory internal consistency of the measurement scales and supported their use in subsequent analysis (Kwamboka & Sang, 2019; Awan et al., 2022; Hammer et al., 2021).

Measurement, Data Analysis and Empirical Model

The study operationalised AI-driven stakeholder management through four dimensions: machine learning, AI-based communication, AI mapping tools, and AI-driven monitoring and evaluation. Project sustainability was conceptualised through the economic, social and environmental dimensions of the Triple Bottom Line. The measurement logic therefore maintained consistency between the theoretical framework and empirical analysis, while enabling each AI dimension to be assessed as a distinct predictor of sustainability (Elkington, 1997; Freeman, 1984; Martínez-Peláez et al., 2023).
Quantitative data were analysed using SPSS version 23, employing descriptive and inferential statistics. The empirical model specified project sustainability as a function of the four AI-driven stakeholder-management strategies:

$$\mathbf{SP=\beta_0+\beta_1 ML+\beta_2 AC+\beta_3 AP+\beta_4 ME+\epsilon \ldots\ldots\ldots\

The study's ethical procedures were guided by informed consent, confidentiality, voluntary participation and responsible data management. Participants were informed of the study purpose and their right to withdraw, while identifying information was protected during data handling and reporting. Because AI research also raises concerns regarding privacy, transparency, accountability and responsible data use, the methodological approach was informed by established AI ethics principles and responsible-data scholarship (National Commission, 1979; Jobin et al., 2019; Stahl & Wright, 2018). These safeguards were particularly relevant because the study concerned technology-enabled stakeholder information and organisational decision-making.

Integration of the Quantitative and Qualitative Evidence

The convergent design enabled the two datasets to address the same substantive phenomenon from complementary perspectives. The quantitative component established the magnitude and statistical significance of the relationships among the four AI strategies and project sustainability, while the qualitative component provided explanations concerning stakeholder visibility, communication, monitoring and decision-making. Such integration is consistent with the principle that mixed-methods research should move beyond merely collecting two types of data toward meaningful comparison and interpretation of their respective contributions (Creswell & Plano Clark, 2023; Hirose & Creswell, 2023; DePoy, 2024).

Accordingly, the empirical interpretation did not treat qualitative evidence as a substitute for statistical testing or statistical results as sufficient explanations of implementation realities. Instead, the two datasets were considered jointly when interpreting how AI-driven stakeholder-management strategies related to sustainability. This approach strengthened the study's capacity to connect measurable project outcomes with organisational and stakeholder experiences, while maintaining the direct-effect structure established in the conceptual framework (Chary, 2024; John et al., 2023; Adebayo et al., 2024).

Research Results of Ai-Driven Stakeholder Management Strategies

Response Rate and Respondent Characteristics

Of the 138 questionnaires administered across the selected Agriculture and Food Authority (AFA) departments, 103 were fully completed and returned, representing a response rate of 74.6%, while 35 questionnaires (25.4%) were not returned. The 103 completed questionnaires constituted the quantitative dataset used in the descriptive and inferential analyses. The response level provided a sufficiently substantive empirical basis for examining AI-driven stakeholder management and project sustainability, particularly because the respondents were drawn from project management, agricultural operations, policy and strategy, monitoring and evaluation, and administrative functions. In applied project-management research, adequate response levels strengthen the credibility of empirical interpretation when respondents possess relevant institutional and operational knowledge (Creswell & Creswell, 2018; Babbie, 2020; Chary, 2024).

The respondent profile further indicated that the evidence was generated from participants with substantial exposure to agricultural project implementation. The largest age category was 31–40 years (38.8%), followed by 41–50 years (26.2%). Males constituted 60.2% and females 39.8% of respondents. Educationally, 82.5% possessed at least a bachelor's degree, while 41.7% held master's or doctoral qualifications. Project management and agricultural operations accounted for the largest departmental groups, while 58.3% of respondents were strategic or operational managers. In addition, 80.6% had worked on projects for at least two years. Collectively, these characteristics indicate that the responses were obtained largely from participants with the professional exposure required to assess AI-enabled planning, communication, mapping and monitoring processes (Creswell & Creswell, 2018; Ngulube, 2022).

Table 2. Respondent Profile (n = 103)

Characteristic	Dominant categories	n (%)
Age	31–40 years	40 (38.8)
Gender	Male	62 (60.2)
Education	Bachelor's degree	42 (40.8)
Department	Project Management	30 (29.1)
Position	Strategic Manager	32 (31.1)
Project experience	2–5 years	39 (37.9)

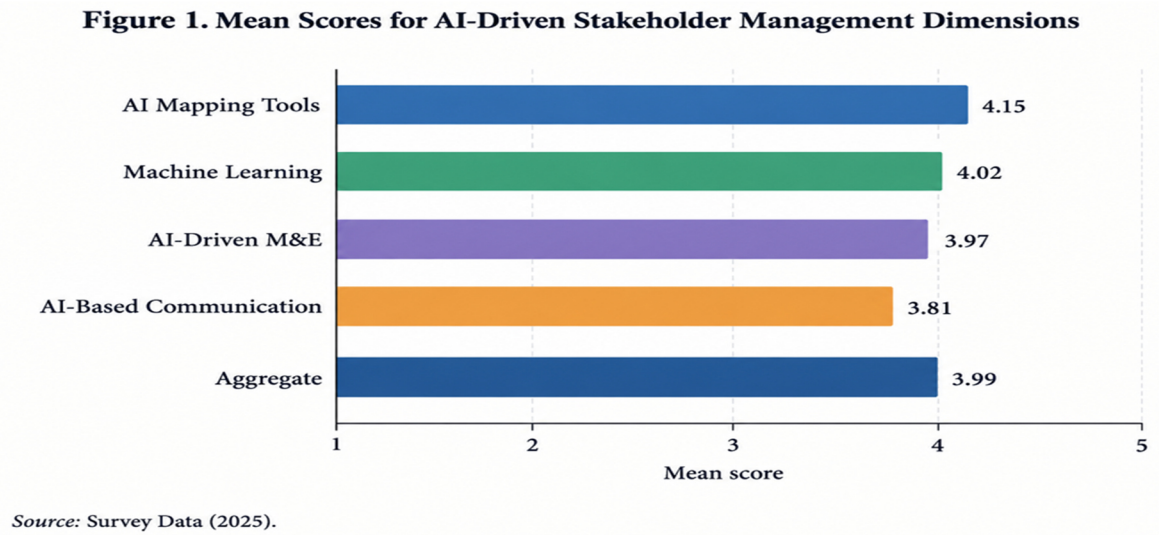
Source: Survey Data (2025).

The profile therefore suggests that the findings reflected perspectives from respondents positioned close to project planning, implementation, coordination and oversight. This was particularly important because AI-driven stakeholder management involves both technical and managerial processes, requiring respondents to understand how digital systems affect decision-making, communication and accountability. The combination of managerial experience, educational attainment and departmental diversity consequently strengthened the contextual relevance of the responses, while the qualitative interviews provided an additional source for explaining how these technologies were experienced in practice (Chary, 2024; Hirose & Creswell, 2023; Adebayo et al., 2024).

Descriptive Results for AI-Driven Stakeholder Management

The four AI-driven stakeholder-management dimensions recorded relatively high mean scores on the five-point scale. AI mapping tools recorded the highest mean (M = 4.15, SD = 0.72), followed by machine learning (M = 4.02, SD = 0.78), AI-driven monitoring and evaluation (M = 3.97, SD = 0.81), and AI-based communication (M = 3.81, SD = 0.88). The aggregate mean of 3.99 (SD = 0.80) indicates an overall positive perception of AI-enabled stakeholder-management practices. The pattern is consistent with literature identifying AI as a mechanism for improving data-driven decision-making, predictive planning, stakeholder responsiveness and resource allocation in project environments (Shang et al., 2023; Martínez-Peláez et al., 2023; Moinuddin et al., 2024).

Figure 2. Mean Scores for AI-Driven Stakeholder Management Dimensions



Source: Survey Data (2025).

Machine learning recorded a mean of 4.02 (SD = 0.78), indicating broad agreement that predictive analytics and risk modelling supported agricultural project planning and efficiency. This quantitative result was reinforced by interview evidence emphasizing predictive intelligence, particularly the ability to identify seasonal risks and anticipate disruptions before they affected project operations. The finding corresponds with research associating AI and machine learning with predictive decision-making, food-security planning and improved resource management (Gideon, 2024; Sarku et al., 2023; Kaur et al., 2024). The convergence between the quantitative rating and qualitative accounts therefore suggests that the perceived value of machine learning was not restricted to technological novelty but was associated with anticipatory project management.
AI-based communication obtained the lowest, although still positive, mean score (M = 3.81, SD = 0.88). The relatively larger standard deviation suggests greater variation in respondents' experiences with digital communication than with mapping and predictive applications. Qualitative evidence provided an explanation for this variation: respondents identified virtual assistants, automated feedback mechanisms and digital communication platforms as improving responsiveness and reaching geographically dispersed stakeholders, while also identifying concerns relating to digital infrastructure, privacy and cultural responsiveness. These findings reflect the dual character of AI adoption identified in the literature, where communication technologies can improve inclusion and information flows but may remain constrained by infrastructure, digital capability and socio-ethical considerations (Adebayo et al., 2024; Moinuddin et al., 2024; Wakunuma et al., 2020).

AI mapping tools produced the highest mean (M = 4.15, SD = 0.72), suggesting strong perceived utility in spatial planning, land-use monitoring and resource allocation. Interview participants similarly described geospatial visualization as useful for clarifying boundaries, identifying

degraded areas and reducing potential stakeholder conflicts. The quantitative and qualitative results consequently converge around the capacity of spatial technologies to make project information more visible and actionable. This interpretation is consistent with research linking AI-enabled mapping, geospatial analysis and environmental intelligence with improved agricultural planning, resource optimization and sustainability (Gryshova et al., 2024; Tandon & Shaheen, 2024; Chukwuma et al., 2024).

AI-driven monitoring and evaluation recorded a mean of 3.97 (SD = 0.81). Although its descriptive score was below machine learning and mapping, the qualitative evidence indicated that real-time dashboards and automated monitoring were particularly important for adaptive management. Respondents reported that real-time information enabled project teams to identify emerging problems, adjust interventions and strengthen reporting. This finding is consistent with arguments that AI-supported monitoring can establish continuous learning and feedback mechanisms, improving responsiveness and accountability within complex project environments (Hofmann et al., 2020; Chisika et al., 2023; Gryshova et al., 2024).

Descriptive Results for Project Sustainability

Project sustainability produced an aggregate mean of 4.05 (SD = 0.75). Environmental sustainability recorded the highest mean (M = 4.17, SD = 0.69), followed by economic sustainability (M = 4.08, SD = 0.74), while social sustainability recorded the comparatively lower mean (M = 3.91, SD = 0.81). The pattern reflects the multidimensional character of sustainability proposed by the Triple Bottom Line perspective, in which economic viability, social responsibility and environmental stewardship constitute interconnected dimensions of sustainable development (Elkington, 1997; Mubangizi, 2024; Chisika et al., 2023).

Table 3. Descriptive Statistics for Project Sustainability

Sustainability dimension	Mean	SD	Interpretation
Environmental	4.17	0.69	Highest perceived performance
Economic	4.08	0.74	High perceived performance
Social	3.91	0.81	Positive but comparatively weaker
Aggregate	**4.05**	**0.75**	**Positive overall perception**

Source: Survey Data (2025).

The relatively high environmental score suggests that respondents perceived AI-enabled agricultural projects as increasingly attentive to environmental management, including land, water and climate-related considerations. The economic score similarly indicates perceived improvements in resource efficiency and project viability. However, the lower social score points to a comparatively greater challenge in achieving inclusion, participation and equitable stakeholder engagement. This distinction is theoretically important because technological capacity alone does not guarantee socially sustainable outcomes; stakeholder participation, institutional

responsiveness and community ownership remain essential components of sustainable agricultural development (Gikunda, 2024; Gryshova et al., 2024; Adebayo et al., 2024).

Inferential Results

Multiple linear regression was used to determine the combined and individual effects of machine learning, AI-based communication, AI mapping tools and AI-driven monitoring and evaluation on overall project sustainability. The analysis was based on 103 complete observations. The model produced R = .826, R^2 = .682 and adjusted R^2 = .673, indicating that the four predictors jointly accounted for 68.2% of the observed variance in project sustainability. The ANOVA result was statistically significant, $F(4, 98) = 52.59$, $p < .001$, demonstrating that the predictor set, taken together, significantly explained variation in sustainability outcomes. The Durbin–Watson statistic of 1.981 was also consistent with independent residuals. The magnitude of explained variance is compatible with literature emphasizing the contribution of data-driven technologies, intelligent decision systems and digital coordination to sustainable project performance (Shang et al., 2023; Martínez-Peláez et al., 2023; Kar et al., 2022).

Table 4. Multiple Regression Results

Predictor	B	β	t	p
Machine learning	0.314	0.322	4.617	< .001
AI-based communication	0.245	0.228	3.311	.001
AI mapping tools	0.196	0.187	2.841	.005
AI-driven M&E	0.381	0.389	6.246	< .001
Model	**R = .826 R^2 = .682 F(4,98) = 52.59 p < .001**			

Source: Survey Data (2025).

All four predictors were statistically significant and positively associated with project sustainability. AI-driven M&E had the largest standardized coefficient ($\beta = .389$, $p < .001$), followed by machine learning ($\beta = .322$, $p < .001$), AI-based communication ($\beta = .228$, $p = .001$), and AI mapping tools ($\beta = .187$, $p = .005$). The coefficients therefore indicate differentiated contributions within a common direct-effects model rather than a hierarchy of independent mechanisms. These results support previous findings that predictive analytics, AI-enabled monitoring, communication systems and spatial technologies can improve project responsiveness, resource management and sustainability when integrated into organizational processes (Adebayo et al., 2024; Gryshova et al., 2024; Chukwuma et al., 2024).

The estimated regression equation was:

$$\mathbf{SP = 0.721 + 0.314ML + 0.245AC + 0.196AP + 0.381ME + \varepsilon}$$

where SP represents project sustainability, ML represents machine learning, AC represents AI-based communication, AP represents AI mapping tools, and ME represents AI-driven monitoring and evaluation. The equation demonstrates that, holding the other predictors constant, a one-unit increase in each AI dimension was associated with a positive change in the predicted sustainability score. However, the results should be interpreted as statistical associations within the observed

model rather than as proof of causal effects, particularly because the study employed a cross-sectional design (Creswell & Creswell, 2018; Creswell & Plano Clark, 2023; Hirose & Creswell, 2023).

Integrated Qualitative Findings

The qualitative analysis generated four closely related themes: predictive intelligence, transparent communication, geo-visualization for planning, and real-time monitoring and evaluation. These themes corresponded closely with the four quantitative constructs, providing convergence between the datasets. Participants described machine learning as useful for anticipating seasonal shocks and planning inputs, AI communication as improving feedback from remote stakeholders, mapping tools as clarifying spatial information and reducing disputes, and AI-driven M&E as facilitating rapid corrective action. The convergence supports the methodological rationale for combining quantitative and qualitative evidence in a convergent mixed-methods design (Creswell & Creswell, 2018; Oranga, 2025; Hirose & Creswell, 2023).

Table 5. Integrated Quantitative–Qualitative Findings

AI strategy	Quantitative evidence	Qualitative interpretation	Sustainability implication
Machine learning	$M = 4.02$; $\beta = .322$, $p < .001$	Predictive intelligence and risk anticipation	Economic resilience and planning
AI communication	$M = 3.81$; $\beta = .228$, $p = .001$	Faster feedback and wider stakeholder reach	Social inclusion and responsiveness
AI mapping	$M = 4.15$; $\beta = .187$, $p = .005$	Geo-visualization and boundary clarification	Environmental planning
AI-driven M&E	$M = 3.97$; $\beta = .389$, $p < .001$	Real-time dashboards and adaptive learning	Accountability and overall sustainability

Source: Survey Data and NVivo Analysis (2025).

The qualitative evidence also introduced important contextual qualifications to the positive statistical results. Participants identified data privacy, cultural responsiveness, interoperability and uneven digital capacity as conditions that could limit effective AI implementation. Consequently, the results do not support a technologically deterministic interpretation in which AI automatically produces sustainability. Rather, they indicate that the value of AI depends on how effectively technological systems are integrated with institutional processes, stakeholder capabilities and contextual knowledge. This interpretation is consistent with research emphasizing infrastructure, skills, governance and ethical safeguards as prerequisites for responsible AI implementation in developing-country contexts (Aderibigbe et al., 2023; Moinuddin et al., 2024; Wakunuma et al., 2020).

DISCUSSION AND INTERPRETATION OF FINDINGS

The central finding was that AI-driven stakeholder management strategies were significantly associated with project sustainability, with the four predictors jointly explaining 68.2% of the variance. This provides empirical support for positioning AI not merely as an administrative technology but as an organizational capability that can strengthen planning, communication, spatial intelligence and continuous monitoring. The finding extends stakeholder-oriented perspectives by demonstrating how digital systems can facilitate the identification, coordination and responsiveness of stakeholders within complex agricultural projects (Freeman, 1984; Martínez-Peláez et al., 2023; Shang et al., 2023). It also complements the Triple Bottom Line perspective by showing how AI-enabled processes can support economic, social and environmental dimensions simultaneously (Elkington, 1997; Mubangizi, 2024; Kar et al., 2022).

Machine Learning and Sustainability

Machine learning had a positive and statistically significant relationship with project sustainability ($\beta = .322$, $p < .001$). The result indicates that predictive capabilities were associated with stronger sustainability outcomes, particularly through improved anticipation of risks, planning and resource allocation. Qualitative respondents reinforced this interpretation by describing predictive systems as useful for anticipating seasonal shocks and improving input planning. The finding corresponds with evidence that AI-supported predictive analytics can improve decision-making and adaptive management in agricultural and food-security systems (Sarku et al., 2023; Gideon, 2024; Kaur et al., 2024).

From the theoretical perspective, the finding complements both Stakeholder Theory and the Technology Acceptance Model. Predictive information improves the ability of project managers to anticipate stakeholder and operational requirements, while perceived usefulness provides a basis for continued adoption of AI systems (Freeman, 1984; Davis, 1989; Shang et al., 2023). Nevertheless, the qualitative findings suggest that predictive capacity is valuable only when users possess the skills and institutional support required to interpret and act on generated information. Thus, the contribution of machine learning lies not simply in prediction but in converting prediction into timely managerial action.

AI-Based Communication and Social Sustainability

AI-based communication was positively and significantly associated with project sustainability ($\beta = .228$, $p = .001$). Although it recorded the lowest descriptive mean among the four AI strategies, the inferential result indicates that communication remained a meaningful predictor when the other dimensions were statistically controlled. The qualitative evidence explained this relationship through improved feedback, accessibility and responsiveness, particularly for geographically dispersed agricultural stakeholders. These findings are consistent with research linking digital

communication to improved stakeholder engagement, transparency and coordination (Adebayo et al., 2024; Moinuddin et al., 2024; Pigola et al., 2021).

The relatively lower mean and higher variability for AI communication are equally important. They suggest that the social benefits of AI may be more context-dependent than its technical applications in mapping or prediction. Issues of infrastructure, digital literacy, privacy and cultural appropriateness can influence whether automated communication is experienced as inclusive or exclusionary. This finding therefore reinforces the argument that responsible AI requires attention to social context and stakeholder capabilities rather than technological functionality alone (Aderibigbe et al., 2023; Wakunuma et al., 2020; Jobin et al., 2019).

AI Mapping Tools and Environmental Sustainability

AI mapping tools recorded the highest descriptive mean ($M = 4.15$, $SD = 0.72$) and a positive significant regression coefficient ($\beta = .187$, $p = .005$). Respondents associated mapping technologies with land-use planning, boundary clarification, resource logistics and environmental monitoring. The qualitative evidence strengthened this interpretation by showing how spatial visualization could reduce uncertainty and support interventions based on geographically differentiated conditions. These findings align with studies identifying AI-enabled geospatial systems as important instruments for environmental monitoring, resource optimization and climate-smart agricultural planning (Tandon & Shaheen, 2024; Gryshova et al., 2024; Chukwuma et al., 2024).

The finding is particularly consistent with the environmental component of the Triple Bottom Line. Spatial intelligence allows project managers to connect project decisions with physical environmental conditions, thereby supporting more informed resource allocation and ecological management. However, the relatively smaller standardized coefficient compared with M&E and machine learning indicates that mapping should be interpreted as one component of an integrated sustainability system rather than a sufficient condition for sustainable outcomes (Elkington, 1997; Ali et al., 2024; Danish & Senjyu, 2023).

AI-Driven Monitoring and Evaluation and Sustainability

AI-driven M&E produced the strongest standardized coefficient in the model ($\beta = .389$, $p < .001$), indicating the largest unique statistical contribution among the four predictors. Qualitative evidence provided a substantive explanation for this result: respondents emphasized real-time dashboards, automated reporting, feedback loops and rapid adjustment of project activities. The finding suggests that continuous information flows may strengthen sustainability by enabling projects to identify deviations and respond before emerging problems become more difficult or costly to address (Hofmann et al., 2020; Gryshova et al., 2024; Chisika et al., 2023).

The result also reinforces the stakeholder-management function of M&E. Monitoring systems do not merely measure project performance; when designed as feedback mechanisms, they connect beneficiaries, implementers, managers and decision-makers through a continuous information cycle. This interpretation is compatible with Stakeholder Theory because effective stakeholder relationships require responsiveness to stakeholder interests and project effects (Freeman, 1984; Mitchell et al., 1997; Adebayo et al., 2024). It also complements the Technology Acceptance Model because the continued use of AI-enabled M&E depends on perceived usefulness and the capacity of users to incorporate system outputs into project decisions (Davis, 1989; Moinuddin et al., 2024; Shang et al., 2023).

Integrated Interpretation

The combined quantitative and qualitative evidence therefore supports an integrated interpretation in which AI-driven stakeholder management contributes to sustainability through four complementary functions: prediction, communication, spatial intelligence and adaptive monitoring. The regression results establish the statistical significance of the four dimensions, while the interviews explain the operational pathways through which respondents experienced these technologies. Such convergence strengthens the interpretation because the qualitative findings did not contradict the statistical pattern; rather, they contextualized it by revealing the institutional and ethical conditions under which AI was perceived to create value (Creswell & Plano Clark, 2023; Hirose & Creswell, 2023; Oranga, 2025).

Importantly, the results should not be interpreted as demonstrating that AI independently guarantees economic, social or environmental sustainability. The study measured overall project sustainability in the reported regression model, while the descriptive analysis separately assessed economic, social and environmental dimensions. Consequently, the inferential evidence establishes significant relationships between the four AI predictors and aggregate project sustainability, whereas the dimension-specific findings provide descriptive evidence concerning economic, social and environmental performance. This distinction preserves analytical precision and avoids attributing separate causal effects to individual sustainability dimensions that were not independently modelled.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The study concluded that AI-driven stakeholder management strategies were significantly associated with the sustainability of agriculture and food-security projects in Kenya. The combined model explained 68.2% of the variance in project sustainability, while all four AI dimensions recorded positive and statistically significant coefficients. The findings consequently provide empirical support for integrating AI into stakeholder-management processes rather than treating it

solely as a technical or administrative innovation (Shang et al., 2023; Martínez-Peláez et al., 2023; Kar et al., 2022).

Regarding machine learning, the study concluded that predictive intelligence constituted an important component of sustainable project management. Its significant coefficient ($\beta = .322$, $p < .001$), together with qualitative evidence concerning risk anticipation and seasonal planning, indicates that predictive applications can strengthen evidence-based planning and resource management. In relation to AI-based communication, the study found a significant positive association with sustainability ($\beta = .228$, $p = .001$), while the qualitative findings emphasized improved feedback and stakeholder responsiveness (Gideon, 2024; Sarku et al., 2023; Adebayo et al., 2024).

The study further concluded that AI mapping tools were positively associated with sustainability ($\beta = .187$, $p = .005$), with the highest descriptive rating among the four AI dimensions. Their principal contribution was reflected in spatial planning, environmental monitoring and improved visualization of project conditions. AI-driven M&E produced the strongest standardized coefficient ($\beta = .389$, $p < .001$), suggesting that continuous monitoring, real-time feedback and adaptive decision-making constituted particularly important elements of sustainable project management. These findings reinforce the complementary relevance of environmental intelligence, predictive analytics and continuous evaluation within agricultural project systems (Gryshova et al., 2024; Tandon & Shaheen, 2024; Hofmann et al., 2020).

Overall, the study concludes that AI should be understood as an enabling capability whose sustainability value depends on institutional integration, human capacity, stakeholder participation and responsible data practices. The comparatively lower social sustainability score and qualitative concerns concerning privacy, cultural responsiveness and digital capacity indicate that technological expansion should be accompanied by inclusive governance and capacity development. AI should therefore complement rather than displace local knowledge and stakeholder participation within agricultural and food-security projects (Wakunuma et al., 2020; Aderibigbe et al., 2023; Adebayo et al., 2024).

Recommendations

Government agricultural institutions should institutionalize AI-enabled predictive analytics and monitoring systems for agricultural planning, risk forecasting, resource allocation and food-security interventions. Particular emphasis should be placed on systems capable of translating predictive information into actionable managerial decisions. Such institutionalization should be accompanied by responsible-AI standards addressing data governance, transparency, interoperability and accountability, thereby aligning technological adoption with agricultural policy and sustainability objectives (Aderibigbe et al., 2023; Moinuddin et al., 2024; Jobin et al., 2019).

Development partners should strengthen inclusive AI-based communication through multilingual platforms, automated feedback mechanisms and participatory digital channels that extend engagement to geographically remote and marginalized stakeholder groups. AI tools should be co-designed with communities so that local knowledge, cultural practices and stakeholder priorities are incorporated into system development and implementation. Such approaches would help address the social sustainability gap identified in the study while improving trust and institutional legitimacy (Adebayo et al., 2024; Wakunuma et al., 2020; Pigola et al., 2021).
Environmental agencies and research institutions should expand the use of geospatial AI for land-use planning, soil and water monitoring, climate-risk assessment and environmental protection. Interoperable systems linking spatial data, satellite information and agricultural project databases would improve the availability of evidence for environmental decision-making. The recommendation follows the strong descriptive performance of AI mapping tools and their statistically significant association with overall project sustainability (Tandon & Shaheen, 2024; Gryshova et al., 2024; Ali et al., 2024).

Project managers and M&E units should prioritize real-time AI-enabled dashboards, automated reporting, anomaly detection and predictive performance monitoring. Given that AI-driven M&E recorded the largest standardized coefficient in the regression model, strengthening this function could improve adaptive management, accountability and evidence-based decision-making. However, implementation should include staff training, system interoperability and human oversight so that automated outputs remain subject to professional judgement and stakeholder validation (Hofmann et al., 2020; Shang et al., 2023; Chisika et al., 2023).

Across all implementing institutions, continuous capacity development should accompany AI deployment. Managers, agricultural officers, M&E personnel and community-facing staff require practical competencies in interpreting AI outputs, protecting data, communicating technological decisions and identifying inappropriate or biased system outputs. This recommendation is supported by the qualitative evidence concerning capacity and interoperability challenges and by literature identifying infrastructure, skills and institutional readiness as major determinants of successful AI implementation in developing contexts (Aderibigbe et al., 2023; Moinuddin et al., 2024; Davis, 1989).

Suggestions for Further Research

Future research should employ longitudinal designs to establish how AI adoption and sustainability outcomes change over time and to provide stronger evidence concerning temporal relationships. Comparative studies across counties and agricultural subsectors could further determine whether the observed relationships vary according to institutional capacity, infrastructure and project characteristics. Qualitative and ethnographic research would also be valuable for examining community trust, cultural responsiveness, privacy and local knowledge in

AI-enabled stakeholder management, particularly because these issues were visible in the present qualitative findings (Creswell & Creswell, 2018; Creswell & Plano Clark, 2023; Hirose & Creswell, 2023).

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