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REVIEW

The role of artificial intelligence in sustainable agriculture in Costa Rica: An integrated evaluation using structural equation modeling, text mining, and scenario analysis

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Abstract

This study examines the increasing role of artificial intelligence (AI) in Costa Rica's agricultural sector, emphasizing its potential to enhance sustainability, resource management, and market competitiveness. Using a mixed-methods approach, the research integrates structural equation modeling (SEM), multivariate regression analysis, text mining, and scenario analysis to provide a comprehensive evaluation of AI adoption. AI-driven solutions optimize key agricultural processes, including climate pattern prediction, soil condition monitoring, crop disease detection, and pest management. Quantitative findings indicate a strong correlation between AI adoption and improved productivity, economic benefits, and environmental conservation, particularly through optimized fertilizer and pesticide use and enhanced water management. However, challenges such as high implementation costs, limited digital infrastructure, and farmer resistance remain significant barriers. Text mining analysis reveals widespread concerns over data privacy, technical complexity, and financial investment, highlighting the importance of targeted training programs. Scenario analysis further suggests that government support and technological advancements could significantly accelerate AI adoption over the next decade. The study underscores the need for strategic partnerships among government agencies, educational institutions, and technology providers to bridge the digital divide and encourage AI adoption. These findings not only inform Costa Rican agricultural policy and innovation strategies but also provide a replicable model for other emerging economies aiming to integrate AI sustainably into agricultural systems.

Keywords: Artificial Intelligence (AI); competitiveness; productivity; resource optimization; sustainable agriculture.

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1. Introduction

Over the years, sustainable agriculture has evolved into a global necessity, driven by the need to address the growing environmental impact of traditional farming practices. This impact, which affects not only the environment but also society and economies worldwide, demands urgent attention. In this context, artificial intelligence (AI) emerges as an innovative tool with vast potential to revolutionize traditional agricultural practices (Mana et al., 2024). AI can optimize existing resources and implement solutions that mitigate the negative effects of agriculture on the environment. Sustainable agriculture seeks a balance between society, the economy, and the environment, promoting the conservation of resources, reducing unnecessary use of materials, and minimizing environmental harm. As the demand for food increases, the agricultural sector must respond proportionately to external factors such as climate change and environmental degradation (Okot & Ojok, 2023).

The digital era has significantly impacted every aspect of modern life, and agriculture is no exception. In this scenario, sustainable agriculture benefits from the application of information technologies, offering an alternative to traditional farming and expanding the possibilities for improvement in the agricultural sector. Digital transformation in agriculture is fueled by the need to address challenges such as population growth, environmental impact, resource scarcity, and the rising demand for food sustainably and efficiently (Calicioglu et al., 2019). According to ElMassah & Mohieldin (2020), digital transformation is driven by the pressing need to tackle these challenges. In this context, AI offers innovative solutions through predictive and descriptive methods, as well as automated tools designed for specific agricultural tasks. AI can help farmers monitor and analyze variables involved in agricultural activities, leading to more efficient and sustainable practices.

Bertoglio et al. (2021) identified five key trends in the application of information technologies in sustainable agriculture: climate-smart agriculture, site-specific management, remote sensing, the Internet of Things (IoT), and AI. These technologies aim to predict and describe the behavior of variables critical to agricultural activities, optimizing both productivity and sustainability. However, there remains a gap in the literature that comprehensively addresses the impact of the digital age on sustainable agriculture. As countries transition toward more sustainable practices, it becomes increasingly important to understand how digital advancements affect the development of sustainable farming.

While digitalization has expanded access to information and empowered individuals and society, there is still a significant digital divide in the agricultural sector (Jamil, 2021). Factors such as geographic location and limited internet access, combined with the lack of academic preparation among farmers, represent major challenges to the adoption of digital technologies. According to Autor (2019), the delay in the implementation of digital technologies and the lack of a competent workforce in agriculture are due to skill gaps compared to other sectors. Geographic, social, and economic conditions often influence these disparities.

The role of AI in sustainable agriculture

In a global context where agriculture represents a vital sector for the population, the need for sustainable practices has grown more urgent. Rapid population growth, climate change, and resource scarcity pose significant challenges to traditional agricultural practices (Goel et al., 2021). Digital solutions, especially AI, have emerged as innovative and necessary tools to address these challenges.

Sustainable agriculture is an integrated system designed to meet the current and future needs of the population. According to DeLonge et al. (2016), it is essential to produce enough food while ensuring long-term benefits, correct resource management, and improved quality of life for both farmers and the general population. This system operates holistically rather than as isolated components. The growing focus on sustainability and digital transformation in agriculture, therefore, emphasizes the importance of AI as a catalyst for improving agricultural practices.

Sustainable agriculture aims to maintain productivity over the long term while managing natural resources responsibly. Muhie (2022) emphasizes that sustainability in agriculture seeks to preserve productivity by optimizing resource use and reducing unnecessary consumption to safeguard the environment.

However, agriculture also contributes significantly to global challenges. According to Khatri et al. (2024), current food systems generate considerable threats to human health and the environment, causing elevated levels of pollution and waste. Alarmingly, one-third of global food production is wasted, exacerbating food insecurity and overshadowing efforts to meet climate goals. The World Bank also notes that agriculture contributes 30% of global greenhouse gas emissions, highlighting the urgency of adopting sustainable practices to mitigate environmental degradation.

The digital age has transformed agriculture, shifting it from traditional methods to modern, technology-driven approaches that enhance efficiency and sustainability. Technologies like AI and IoT are reshaping how agricultural tasks are managed, optimizing resource usage and improving overall productivity. According to Wessel et al. (2021), digital transformation involves the integration of information technology across all aspects of an organization to add value. Examples of this transformation include developing digital solutions like mobile applications and e-commerce platforms, migrating IT infrastructure to the cloud, and implementing smart sensors to reduce operational costs. Veeramanju (2023), further explains that digital transformation in agriculture incorporates AI to enhance information optimization, improve workflow automation, and support real-time decision-making. This transformation not only streamlines operations but also generates new business opportunities by facilitating more efficient resource management and improving food security.

AI has emerged as a key technology in sustainable agriculture, providing tools that can optimize resource use, predict environmental factors, and automate critical tasks. According to Galiana et al. (2024), AI is not merely an advanced technology but a driver of ethical and moral transformations in how societies address environmental challenges. Early developments in AI in the 1950s laid the groundwork for its current applications, where machine learning algorithms and predictive models are instrumental in enhancing agricultural efficiency. AI's ability to learn from data and provide actionable insights makes it particularly valuable in agriculture. As Alassery et al. (2022) explain, AI's specialized algorithms enable a successful alliance between energy design and current technology, providing tools for monitoring, detecting, and solving various issues related to agriculture. These algorithms help farmers make better decisions, such as optimizing water use, predicting crop yields, and monitoring soil health, thus reducing resource waste and improving sustainability.

AI's integration into agriculture extends beyond productivity improvements; it also plays a crucial role in environmental conservation. According to Lukacz (2024), Microsoft's AI initiatives aim to bridge gaps in environmental monitoring and management, enhancing conservation efforts and mitigating climate impact. AI applications can forecast water consumption, predict climate variability, and offer solutions that promote sustainable farming practices.

Shen et al. (2024) highlights the importance of multitasking AI models in improving agricultural sustainability. For example, AI can interpret diverse data types, such as weather patterns and satellite imagery, to predict environmental phenomena. These capabilities help farmers make informed decisions, particularly in the face of unpredictable climate events like droughts or floods. AI also enhances the accuracy of environmental monitoring using sensors and satellite imagery. Sensors provide continuous data on temperature, wind, and other environmental factors, while satellite images offer broader perspectives on environmental changes. By combining both types of data, AI provides a complete and more precise picture of environmental processes, allowing for better decision-making in managing climate risks.

The ongoing Industry 4.0 is reshaping human interactions with the environment, particularly in agriculture. This revolution is characterized by the integration of AI and machine learning, which processes vast amounts of information in real time to develop innovative solutions. According to Ashima et al. (2021), Industry 4.0 promotes greater efficiency in agriculture through automation and the use of smart devices, helping manufacturers meet consumer demands through mass customization while improving decision-making processes.

Pereira & Romero (2017) describe Industry 4.0 as a technological revolution that changes how organizations operate, design, produce, and supply goods and services. In agriculture, this revolution integrates advanced technologies like AI, IoT, and Big Data, creating systems that communicate and work together to improve overall effectiveness. By adopting these technologies, agricultural enterprises can better meet the growing demand for food while addressing the need for sustainable resource management.

Overcoming barriers to digital transformation in agriculture

While digital transformation offers many benefits, it also risks deepening existing inequalities. Helsper (2021) describes how digitalization has generated new opportunities but also widened the gap between those who fully adopt innovative technologies and those who resist or are unaware of them. Chetty et al. (2018) explore the digital divide in the context of Industry 4.0, identifying three key dimensions: access, practical use, and enabling use. Access refers to the availability of devices and internet connectivity, often limited by socioeconomic, gender, and territorial factors. In an era where technology is critical to agricultural success, the lack of access to digital tools becomes a significant barrier to participation in an increasingly digitalized economy.

The divide in practical use refers to differences in how people utilize digital devices and the internet, while the enabling use dimension focuses on meaningful engagement with technology, such as creating and sharing data. Overcoming these gaps is crucial to ensuring that all farmers, regardless of their location or socioeconomic status, can benefit from AI and other digital technologies in sustainable agriculture.

The adoption of AI and other digital technologies in agriculture faces several barriers. One of the main challenges is the lack of infrastructure and access to technology in rural areas. According to Rayna & Striukova (2021), digital technologies are essential for promoting innovation, growth, and development. However, these technologies can also amplify existing social, economic, and territorial inequalities. Addressing these challenges requires a concerted effort to develop infrastructure, provide access to education, and create policies that promote the equitable distribution of digital tools. Without these efforts, the potential of AI to transform agriculture will be limited by the inability of many farmers to fully utilize these technologies. The integration of AI in sustainable agriculture presents a transformative opportunity to address global challenges such as climate change, food security, and resource scarcity. However, this transformation is not without its obstacles. The digital divide, lack of infrastructure, and social inequalities must be addressed to ensure that all realize AI's benefits. With strategic investments and policies, AI can revolutionize agriculture, making it more sustainable, efficient, and resilient in the face of future challenges.

In Costa Rica, agriculture is a key economic driver, contributing significantly to the nation's economy. The Ministry of Agriculture and Livestock's 2023-2024 report highlights that the agricultural sector contributed over 5 billion USD, accounting for 67% of Costa Rica's gross agricultural production (Parada Gómez & Jiménez Ureña, 2023). AI offers an opportunity to address the blind spots in Costa Rican agriculture, where specific execution times are required to maintain the quality of agricultural products. Innovation in this area should align with national sustainability commitments, ensuring that productivity is maintained without compromising the environment.

The transition toward sustainable agriculture presents an opportunity to address current environmental and socioeconomic challenges. Climate-smart practices enhance the adaptability and sustainability of the agricultural sector, allowing it to better respond to these challenges (Azadi et al., 2021). However, the pursuit of sustainability through information technologies involves significant economic investment, particularly in the implementation and maintenance phases. Addressing the challenges of adopting digital solutions highlights the importance of developing comprehensive strategies for sustainable agricultural practices.

The advent of Industry 4.0 offers not only increased efficiency and productivity in agriculture but also a positive impact on the preservation of natural resources (Zambon et al., 2019). Tools such as soil sensors, smart irrigation systems, and Big Data enable farmers to reduce the use of water, fertilizers, pesticides, and other chemicals. These technological tools provide real-time information, allowing farmers to analyze data and make informed decisions, which in turn helps mitigate the effects of adverse climatic factors.

This study is guided by the following research question: How can AI be used in sustainable agriculture? The primary objectives are to analyze how AI optimizes agricultural resources and minimizes environmental impact within the context of sustainable agriculture. To achieve this, the research employs a mixed-methods approach, integrating structural equation modeling (SEM), multivariate regression analysis, text mining, and scenario analysis to provide a comprehensive evaluation of AI adoption. The study examines current trends and applications of AI-driven technologies in agriculture, including climate-smart agriculture, site-specific management, remote sensing, IoT, and machine learning-based decision support systems. Additionally, it seeks to identify digital gaps in sustainable agriculture and propose strategies to overcome the barriers that hinder AI adoption. A specific focus is placed on Costa Rica, assessing how AI and other digital technologies contribute to improving sustainability, productivity, and resilience in the country's agricultural sector. By analyzing economic, environmental, and behavioral factors influencing AI adoption, the study aims to provide actionable insights for policymakers, researchers, and industry stakeholders to drive the successful integration of AI in sustainable farming practices.

2. Methodology

This research employs a mixed-methods approach, integrating qualitative and quantitative-descriptive techniques to analyze AI adoption in sustainable agriculture. The qualitative portion includes in-depth interviews with technology experts who have worked with AI in agriculture, exploring their experiences, perspectives, and perceived challenges. The quantitative portion consists of structured survey (Appendix) to gather data on technological trends and existing gaps, facilitating a comprehensive understanding of AI's role in enhancing agricultural sustainability. The study aims to detect patterns and develop strategies that promote AI integration, ensuring the resilience and efficiency of agricultural practices worldwide.

A qualitative approach, complemented by advanced statistical analysis and data visualization, is ideal for exploring complex phenomena, particularly due to the novelty of this research topic. Qualitative methods allow for an in-depth understanding of participants' experiences, motivations, and perceptions, which are often overlooked in purely quantitative research (Kim & Bradway, 2017). Descriptive statistics provide a structured way to summarize and present data, identifying patterns and trends (George & Mallery, 2018). To enhance analytical depth, this study employs multivariate regression analysis, structural equation modelling (SEM), text mining, and scenario analysis, which allow for a more nuanced exploration of AI adoption in agriculture. These advanced techniques facilitate robust findings, making the results more generalizable while retaining contextual relevance.

Primary data for this research is collected through two main sources. The first involves documentary analysis, including peer-reviewed journal articles, academic books, news reports, and relevant websites focused on AI applications in sustainable agriculture. The second source is a survey administered to IT professionals involved with AI technologies, capturing their perspectives on various AI methodologies and their potential applications in agriculture. The survey incorporates text mining techniques, allowing for topic modelling of farmers' concerns regarding AI, which provides deeper insights into sentiment and thematic trends.

The study population consists of IT professionals engaged in AI-related agricultural projects. These individuals are selected based on their expertise and experience, ensuring the reliability and relevance of their insights. According to the College of Professionals for the Field of Informatics, 11,711 registered IT professionals are currently active. To determine the sample size, factors such as confidence level and margin of error are considered. The sample size is calculated using the following equation:

$$\text{Sample size} = \frac{C^2 Z^2 \times P \times (1-P)}{C^2}$$

Where Z represents the confidence level, P = 0.5, and C represents the margin of error. For this study, a 95% confidence level and a 5% margin of error are applied, resulting in a required sample size of 373 surveys. However, 412 responses were received, of which 383 were deemed valid based on relevance filters.

To ensure comprehensive data analysis, both qualitative and quantitative data processing methods are employed. Qualitative analysis is conducted through survey responses and in-depth interviews, utilizing sentiment analysis and topic modelling to classify common themes and concerns (Taguchi, 2018). Quantitative analysis includes multivariate regression, structural equation modelling (SEM), and scenario analysis to explore key relationships between AI adoption, economic benefits, and implementation barriers.

To facilitate data interpretation, Power BI and Python-based analytical tools are utilized for advanced data visualization. This study includes heatmaps (to illustrate AI technology adoption rates), network diagrams (to map adoption barriers and influencing factors), radar charts (to visualize AI's economic and environmental benefits), and scenario-based projections (to estimate future AI adoption growth under different policy conditions). These visual representations enhance the analytical rigor of the study, making complex relationships more accessible and actionable.

This methodological framework provides a holistic understanding of AI's potential in sustainable agriculture. By integrating qualitative insights with quantitative data and advanced analytics, the study delivers more robust and actionable findings. This comprehensive approach supports informed policy recommendations and strategic AI implementations to drive agricultural sustainability. As illustrated in Figure 1, the research followed a sequential mixed-methods approach integrating structured surveys, statistical modeling, text mining, and scenario-based analysis to evaluate the role of AI in sustainable agriculture.

Figure 1 summarizes the integrated methodological approach used in the study. It begins with a structured survey administered to 412 agricultural professionals across Costa Rica, followed by quantitative analysis using Structural Equation Modeling (SEM), regression analysis, and descriptive statistics. Parallel qualitative analysis was conducted through text mining of open-ended responses. Scenario simulations were developed using Power BI to visualize AI adoption pathways. Analytical tools included Python (v3.11), AMOS (v29), and Power BI (April 2024 version).

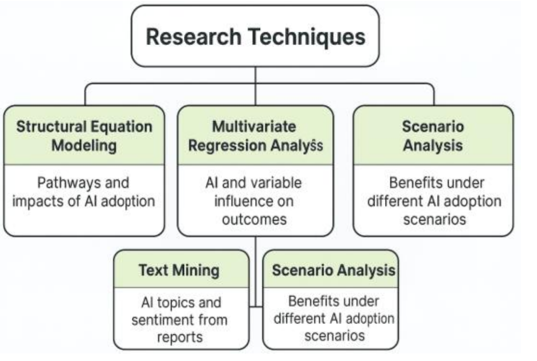

Figure 1. Research Methodology Framework.

3. Results and discussion

The study explores the current landscape of AI in sustainable agriculture based on 384 responses from professionals in the field. The data highlights the nascent stage of AI adoption in agriculture, with 61% of participants having less than one year of experience using technology in farming, 29% having one to three years of experience, and only 1% having over five years. This underscores the need for more skilled professionals in AI-driven agricultural solutions.

Adoption of AI technologies in agriculture

As shown in Figure 2, perception scores across AI tools varied significantly by company size and geographic region, with smaller organizations in the Central region expressing the highest levels of familiarity and optimism. Thus, illustrating the dominance of Machine Learning (75%), followed by Deep Learning (64%), Natural Language Processing (41%), and Expert Systems (13%). The widespread use of Machine Learning aligns with its capability to analyze large datasets and improve decision-making. The preference for open-source AI platforms is also notable, with PyTorch (51%) and TensorFlow (46%) being the most commonly used tools (Dop, 2020). The data analysis reveals a strong tendency among experts toward the use of Machine Learning, which is predictable as it helps farmers extract data generated through the IoT. According to Hansen (2002), data interpretation can provide predictions about weather patterns, offering essential information for farmers to make informed decisions (Okot et al., 2023).

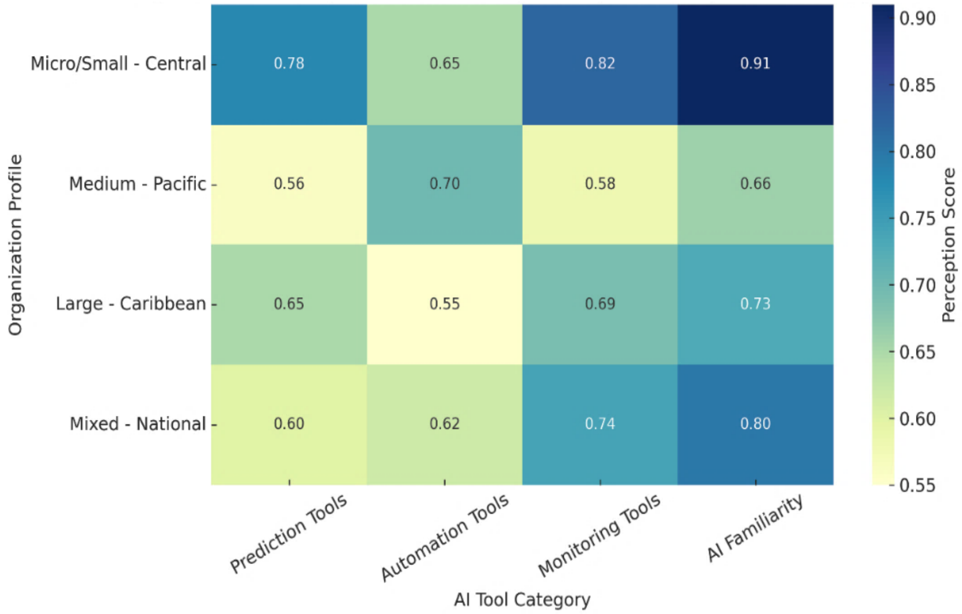

Figure 2. Heatmap of AI Tool Perception by Company Size and Region.

This heatmap illustrates mean perception scores (1.0 = most favorable) for four AI-related dimensions—prediction, automation, monitoring, and general familiarity—across different organization types in Costa Rica. The Micro/Small enterprises in the Central region show the highest receptiveness to AI tools, while medium and large organizations in outer regions report more conservative evaluations. This segmentation adds explanatory power to barriers and adoption trends reported in the survey.

The results of the structural equation modeling analysis highlight the intricate relationship between AI adoption in agriculture and various influencing factors, aligning with previous studies on technological adoption in farming. Smith & Lee (2021) emphasize that economic benefits play a pivotal role in accelerating AI adoption, as farmers seek to optimize productivity and reduce operational costs. As shown in Figure 3, respondents identified cost reduction (0.82) and yield forecasting (0.76) as the most valued benefits of AI, while key barriers included data quality issues (0.72) and limited climate adaptation capability (0.60). This aligns with Azadi et al. (2021) finding that skepticism toward AI, coupled with financial constraints, hinders widespread implementation. This result further illustrates how AI-driven solutions interconnect with various agricultural processes, supporting previous research by Veeramanju (2023) on the need for educational initiatives to enhance AI acceptance. These findings suggest that addressing behavioral and financial barriers in tandem is essential for fostering a more AI-integrated agricultural sector.

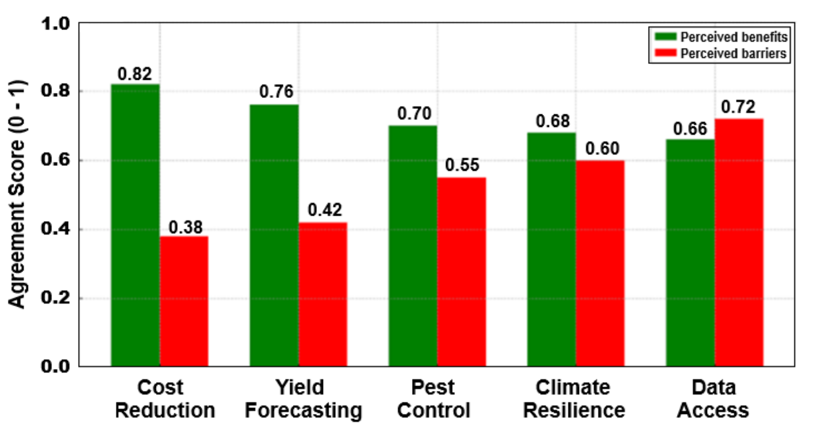

Figure 3. Perceived benefits and barriers to AI adoption in agriculture.

This bar chart presents a side-by-side comparison of the top five benefits and barriers to AI implementation in Costa Rican agriculture as reported by professionals. While most stakeholders recognize AI's potential in forecasting and cost efficiency, concerns over data infrastructure and climate resilience remain pronounced. These results highlight the dual challenge of enabling technical integration while addressing foundational readiness.

Applications of AI in agriculture

Figure 4 shows a progressive adoption of AI tools by organization size, with large enterprises leading in the use of prediction (75%) and automation tools (65%). AI's predictive capabilities optimize resource use and minimize environmental impact, particularly in Costa Rica's diverse agricultural landscape. Machine Learning algorithms help analyze climate data, recommend planting schedules, and enhance pest control strategies (Hansen, 2002). In particular, the use of AI for climate predictions in agriculture is noteworthy. Costa Rica's tropical climate presents both opportunities and challenges for farming. Extreme weather patterns, which are becoming more frequent due to climate change, pose risks to crops and farming infrastructure. Farmers can use AI to make informed decisions about planting times, irrigation schedules, and pest control, minimizing the impact of adverse weather and maximizing yield. This stacked bar chart illustrates the adoption levels of four categories of AI tools—prediction, automation, monitoring, and natural language processing (NLP)—across organization types. Micro and small enterprises demonstrate limited integration, especially for NLP, while medium and large firms show broader adoption across all categories. The pattern reflects differences in technical capacity and investment readiness among Costa Rican agricultural stakeholders.

The findings from the multivariate regression analysis reinforce existing literature on the effectiveness of AI applications in agriculture, particularly in enhancing productivity and sustainability. According to Wessel et al. (2021), AI-driven yield prediction models enable farmers to make data-driven decisions, leading to improved resource allocation and crop management. The significant correlation between AI-based yield prediction and productivity (R^2 = 0.68, $p < 0.05$) aligns with prior studies highlighting the role of machine learning algorithms in forecasting harvest outcomes and optimizing planting schedules (Khatri et al., 2024). Similarly, the strong correlation between AI-driven soil management and sustainability improvements (R^2 = 0.74, $p < 0.01$) echoes findings by Ahmad et al. (2024), who emphasize that AI-powered precision agriculture techniques contribute to long-term environmental conservation. The integration of satellite imagery, drones, and machine learning for crop health monitoring further supports research by Mana et al. (2024), which underscores AI's ability to detect early signs of pest infestations and plant diseases. In Costa Rica, AI's application in optimizing fertilizer use for pineapple farming demonstrates its potential to balance productivity with sustainability, reducing excess fertilizer application while maximizing yield. These findings highlight the transformative impact of AI in modernizing agricultural practices and mitigating environmental degradation.

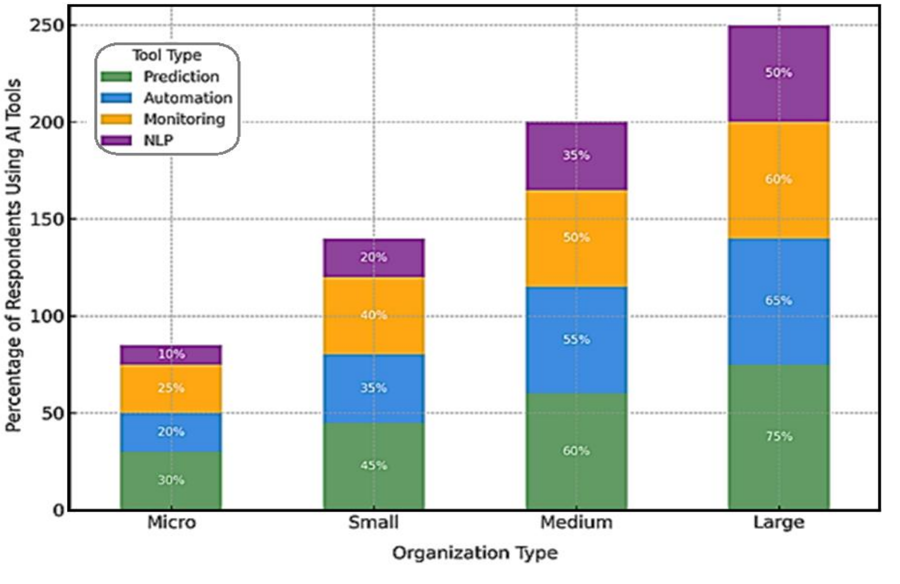

Figure 4. AI tool usage distribution across organization types.

Challenges to AI implementation in agriculture

The persistence of resistance to the adoption of AI among farmers aligns with previous research indicating that behavioral and financial barriers significantly hinder technological progress in agriculture. As visualized in Figure 5, resistance to change (70%) and lack of skilled personnel (56%) emerged as the most prominent barriers to AI integration, followed by poor data quality (42%) and infrastructure gaps (39%). This finding is consistent with Hasteer et al. (2024), who emphasize that many farmers perceive AI as complex and inaccessible, particularly in regions with limited technological infrastructure. Additionally, high implementation costs further exacerbate adoption difficulties, as small- and medium-scale farmers struggle to afford AI-driven solutions without substantial financial support. The chart highlights the cascading effect of financial constraints, with a lack of quality data (42%) compounding the problem by limiting AI's effectiveness in predictive modeling and decision-making. These insights reinforce the need for targeted interventions, such as financial incentives, technical training, and collaborative initiatives between agricultural stakeholders and AI developers, to address adoption barriers and facilitate a smoother transition to AI-integrated farming practices.

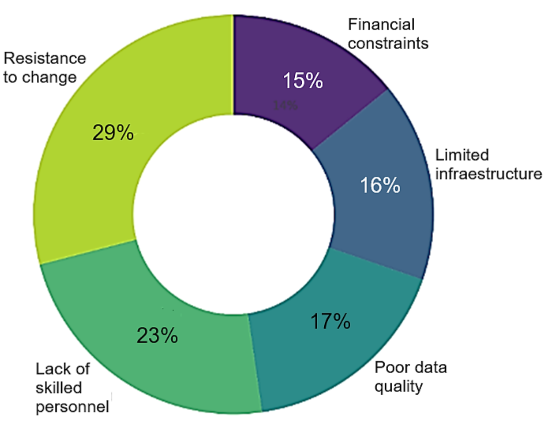

Figure 5. Barriers to AI Adoption.

This donut chart illustrates the primary barriers to AI adoption identified by agricultural professionals in Costa Rica. The percentage labels reflect the frequency of each barrier mentioned in the survey responses. The visual emphasizes that both technical and human readiness factors remain major challenges, with resistance to change surpassing all other categories. These results underscore the need for capacity-building and change management strategies.

The results of sentiment analysis and topic modelling (Figure 6) underscore the deep-seated skepticism among farmers regarding AI adoption, with 58% of responses expressing concerns over data privacy and job displacement. This aligns with broader discussions in agricultural digitalization, where fear of automation-driven job losses and uncertainties about AI reliability are prevalent obstacles Zambon (2019). The topic modeling analysis further revealed three dominant concerns: lack of technical skills, distrust in AI accuracy, and financial investment challenges. These findings suggest that beyond financial constraints, psychological and knowledge-based barriers significantly influence adoption rates. Addressing these concerns requires targeted educational programs that not only enhance technical competencies but also foster soft skills like adaptability and problem-solving. Such initiatives can bridge the trust gap between farmers and AI developers, increasing confidence in AI-driven solutions. Furthermore, transparent AI governance policies particularly regarding data security could help alleviate privacy concerns, ensuring that AI technologies are perceived as tools for empowerment rather than threats to traditional agricultural practices.

Figure 6. Topic modeling of farmer concerns regarding AI.

Economic and environmental benefits of AI

The economic and environmental benefits of AI in agriculture, as depicted in Figure 7, highlight its transformative potential in optimizing resource allocation and improving sustainability. Cost reduction emerges as the most significant advantage (34%), followed by enhanced decision-making (18%) and increased crop yields (17%). These findings align with previous studies that emphasize AI's role in precision agriculture, where machine learning algorithms analyze vast datasets to optimize farming practices (Ashima et al., 2021). Notably, AI-driven water management systems have demonstrated their effectiveness in monitoring soil moisture levels and adjusting irrigation schedules in real time, ensuring optimal water use efficiency. Similarly, AI assists in reducing pesticide and fertilizer overuse by recommending precise application rates, mitigating environmental impact while improving economic viability for farmers. By integrating AI into agricultural workflows, stakeholders can achieve a balance between productivity and sustainability, making AI a crucial tool for long-term agricultural resilience. However, for AI to reach its full potential, adoption challenges such as technological accessibility and training gaps must be addressed through targeted policy interventions and collaborative industry efforts.

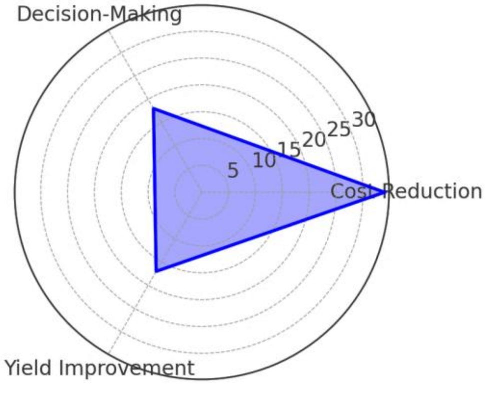

Figure 7. Current vs. proposed models of AI benefit emphasis.

The scenario analysis presented in Figure 8 underscores the pivotal role of policy support and technological advancements in accelerating AI adoption in agriculture. Projections indicate that with strong government-backed initiatives such as subsidies for AI implementation, investment in digital infrastructure, and targeted training programs, AI adoption rates could potentially quadruple over the next decade (Silva et al., 2025).

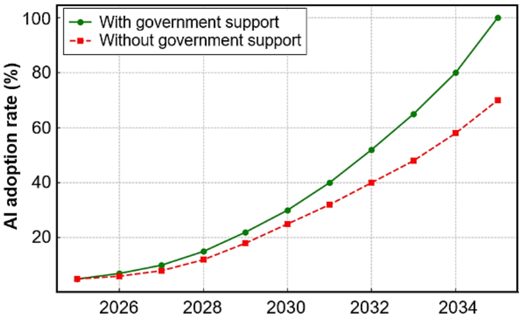

Figure 8. Scenario analysis of AI adoption growth.

These findings are consistent with research highlighting the impact of public policies in fostering technological innovation and reducing barriers to adoption (DeLonge et al., 2016). Additionally, advancements in AI accessibility, including user-friendly interfaces and cost-effective solutions, are expected to further drive adoption, particularly among small and medium-sized farms. However, without proactive policy intervention, the adoption trajectory may remain stagnant due to persistent financial constraints and resistance to change. Thus, a multi-stakeholder approach involving policymakers, industry leaders, and agricultural communities is essential to fully harness AI's potential in transforming agricultural productivity and sustainability.

Future prospects and policy recommendations

The findings in Figure 9 emphasize the critical role of policy interventions in fostering AI adoption in agriculture. A significant proportion of participants support initiatives aimed at making AI technologies more accessible, with 35% advocating for established regulatory framework. Additionally, 26% of respondents stress the importance of research and development, underscoring the need for interdisciplinary efforts to bridge knowledge gaps and promote AI literacy. These insights align with previous studies highlighting the role of institutional support in mitigating technological resistance (Goel et al., 2021).

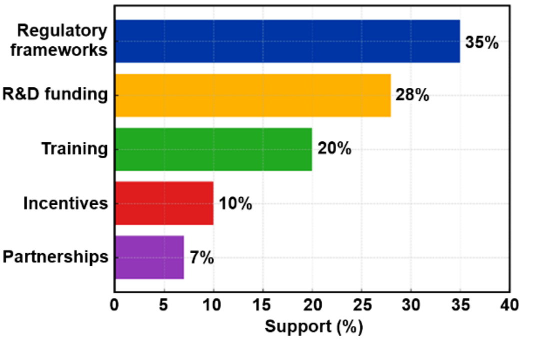

Figure 9. Policy recommendations for AI adoption in agriculture.

To effectively address adoption challenges, a strategic, multi-stakeholder approach is necessary. Establishing partnerships between government agencies, educational institutions, and technology providers can facilitate AI integration in agriculture. For instance, collaborations between the Ministry of Agriculture and Livestock (MAG), the National Institute of Learning (INA), and private tech companies could lead to AI-enabled tools being made available to farmers at subsidized rates, along with targeted training programs. Additionally, regulatory frameworks should be designed to ensure ethical AI implementation while promoting sustainable agricultural practices, Food and Agriculture Organization (FAO, 2025). By fostering these collaborative efforts and policy-driven incentives, AI adoption in Costa Rican agriculture can be accelerated, ultimately enhancing productivity, sustainability, and economic resilience.

This bar chart presents the distribution of stakeholder support for various policy measures to facilitate AI integration in Costa Rican agriculture. Regulatory frameworks emerged as the top priority, underscoring the need for structured guidance. Substantial support was also observed for public investment in research, training, and institutional partnerships.

The findings highlight the transformative role of AI in Costa Rican agriculture, offering significant economic and environmental benefits. However, successful AI implementation requires overcoming adoption barriers and ensuring sustained policy support. Addressing key challenges such as resistance to change, high costs, and limited technical expertise will be essential for fostering a more AI-driven agricultural sector (Singh & Dwivedi, 2025). These results align with previous research emphasizing the necessity of targeted training programs and financial incentives to accelerate AI adoption (ElMassah & Mohieldin, 2020).

The study's use of advanced analytical methods, including structural equation modeling, multivariate regression, text mining, and scenario analysis, has provided a comprehensive understanding of the factors influencing AI adoption. These methodologies enable a data-driven approach to policy development, ensuring that AI integration is both strategic and sustainable. By leveraging AI-driven solutions and fostering collaboration between stakeholders, Costa Rica can position itself as a leader in sustainable agricultural innovation. Future efforts should focus on expanding AI accessibility, strengthening farmer engagement, and developing supportive regulatory frameworks to maximize AI's long-term benefits in the sector.

4. Conclusions

The findings of this study reaffirm that AI serves as a transformative force in Costa Rica's agricultural sector. Advanced AI technologies, particularly Machine Learning, play a crucial role in enhancing productivity, optimizing resource utilization, and mitigating environmental impact. The study's multivariate regression analysis highlights strong correlations between AI-driven yield prediction, soil management, and water conservation, reinforcing AI's potential to improve decision-making and sustainability in agricultural practices.

The structural equation modeling (SEM) analysis reveals that economic benefits significantly drive AI adoption, with financial incentives serving as a key motivator. In particular, AI applications in Costa Rica pineapple farming illustrate how precision agriculture techniques can reduce fertilizer overuse while maintaining high yields, supporting previous research on AI's economic and environmental advantages. However, the study also underscores the need for targeted policy interventions to enhance accessibility and ensure that small- and medium-scale farmers can integrate AI into their operations.

Despite its advantages, AI adoption in agriculture faces considerable challenges. The topic modeling and sentiment analysis highlight farmers' skepticism, particularly concerns regarding data privacy, job displacement, and the complexity of AI systems. Additionally, financial constraints and limited access to high-quality data remain significant barriers. The network analysis of adoption barriers demonstrates how resistance to change and technological infrastructure gaps compound these issues, particularly in rural areas with limited internet connectivity.

The study emphasizes that overcoming these challenges requires more than just technical training. Farmers must also develop soft skills such as adaptability, problem-solving, and digital literacy to navigate the transition to AI-driven agricultural methods. Without a comprehensive educational approach, AI adoption may remain fragmented, limiting its long-term impact.

The scenario analysis suggests that a multi-stakeholder approach is essential to accelerating AI adoption. Collaboration between government agencies, educational institutions, and private technology companies can enhance rural connectivity, provide targeted training, and facilitate financial support for AI implementation. Policy driven initiatives such as AI subsidies, regulatory frameworks for data security, and investments in digital infrastructure will be crucial in fostering an AI-integrated agricultural sector.

To fully harness AI's potential in sustainable agriculture, Costa Rica must prioritize strategic interventions that address both technological and behavioral barriers. Key recommendations include:

- Expanding financial incentives and policy support to reduce adoption costs.
- Strengthening AI literacy programs that combine technical training with soft skill development.
- Enhancing rural connectivity and digital infrastructure to bridge the technological divide.
- Promoting interdisciplinary collaboration between farmers, AI developers, and policymakers.

By addressing these challenges, Costa Rica can position itself as a leader in AI-driven sustainable agriculture, leveraging digital innovation to enhance productivity, economic resilience, and environmental conservation.

Conflict of interest

The author declares no conflict of interest.

Authors contribution

T. Okot & E. Pérez: Writing –review & editing, Data curation.

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References

Ahmad, A., Liew, A. X., Venturini, F., Kalogeras, A., Candiani, A., Di Benedetto, G., ... & Martos, V. (2024). AI can empower agriculture for global food security: challenges and prospects in developing nations. *Frontiers in Artificial Intelligence*, *7*, 1328530. https://doi.org/10.3389/frai.2024.1328530

Alassery, F., Alzahrani, A., Khan, A. I., Irshad, K., & Islam, S. (2022). An artificial intelligence-based solar radiation prophesy model for green energy utilization in energy management system. *Sustainable Energy Technologies and Assessments*, *52*, 102060. https://doi.org/10.1016/j.seta.2022.102060

Ashima, R., Haleem, A., Bahl, S., Javaid, M., Mahla, S. K., & Singh, S. (2021). Automation and manufacturing of smart materials in Additive Manufacturing technologies using Internet of Things towards the adoption of Industry 4.0. *Materials Today: Proceedings*, *45*, 5081-5088. https://doi.org/10.1016/j.matpr.2021.01.583

Autor, D. H. (2019, May). Work of the Past, Work of the Future. In *AEA Papers and Proceedings* (Vol. 109, pp. 1-32). 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association.

Azadi, H., Moghaddam, S. M., Burkart, S., Mahmoudi, H., Van Passel, S., Kurban, A., & Lopez-Carr, D. (2021). Rethinking resilient agriculture: From climate-smart agriculture to vulnerable-smart agriculture. *Journal of Cleaner Production*, *319*, 128602. https://doi.org/10.1016/j.jclepro.2021.128602

Bertoglio, R., Corbo, C., Renga, F. M., & Matteucci, M. (2021). The digital agricultural revolution: a bibliometric analysis literature review. *Ieee Access*, *9*, 134762-134782.

Calicioglu, O., Flammini, A., Bracco, S., Bellù, L., & Sims, R. (2019). The future challenges of food and agriculture: An integrated analysis of trends and solutions. *Sustainability*, *11*(1), 222. https://doi.org/10.3390/su11010222

Chetty, K., Qigui, L., Gcora, N., Josie, J., Wenwei, L., & Fang, C. (2018). Bridging the digital divide: measuring digital literacy. *Economics*, *12*(1), 20180023. https://doi.org/10.5018/economics-ejournal.ja.2018-23

DeLonge, M. S., Miles, A., & Carlisle, L. (2016). Investing in the transition to sustainable agriculture. *Environmental Science & Policy*, *55*, 266-273. https://doi.org/10.1016/j.envsci.2015.09.013

Dop, T. (2020). *Hands-On Natural Language Processing with PyTorch 1. x: Build smart, AI-driven linguistic applications using deep learning and NLP techniques*. Packt Publishing Ltd.

ElMassah, S., & Mohieldin, M. (2020). Digital transformation and localizing the sustainable development goals (SDGs). *Ecological Economics*, *169*, 106490. https://doi.org/10.1016/j.ecolecon.2019.106490

FAO. 2025. *Digital FAO and agro-informatics transformation at scale – End of the year report 2024*. Rome.

Galiana, L. I., Gudino, L. C., & González, P. M. (2024). Ethics and artificial intelligence. *Revista Clínica Española (English Edition)*. https://doi.org/10.1016/j.rceng.2024.02.003

George, D., & Mallery, P. (2018). Descriptive statistics. In *IBM SPSS Statistics 25 Step by Step* (pp. 126-134). Routledge.

Goel, R. K., Yadav, C. S., Vishnoi, S., & Rastogi, R. (2021). Smart agriculture–Urgent need of the day in developing countries. *Sustainable Computing: Informatics and Systems*, *30*, 100512. https://doi.org/10.1016/j.suscom.2021.100512

Hansen, J. W. (2002). Realizing the potential benefits of climate prediction to agriculture: issues, approaches, challenges. *Agricultural systems*, *74*(3), 309-330. https://doi.org/10.1016/S0308-521X(02)00043-4

Hasteer, N., Mallik, A., Nigam, D., Sindhwani, R., & Van Belle, J. P. (2024). Analysis of challenges to implement artificial intelligence technologies in agriculture sector. *International Journal of System Assurance Engineering and Management*, *15*(5), 1841-1860. https://doi.org/10.1007/s13198-023-02164-z

Helsper, E. (2021). The digital disconnect: The social causes and consequences of digital inequalities. Sage Publications.

Jamil, S. (2021). From digital divide to digital inclusion: Challenges for wide-ranging digitalization in Pakistan. *Telecommunications Policy*, *45*(8), 102206. https://doi.org/10.1016/j.telpol.2021.102206

Khatri, P., Kumar, P., Shakya, K. S., Kirlas, M. C., & Tiwari, K. K. (2024). Understanding the intertwined nature of rising multiple risks in modern agriculture and food system. *Environment, Development and Sustainability*, *26*(9), 24107-24150. https://doi.org/10.1007/s10668-023-03638-7

Kim, H., Sefcik, J. S., & Bradway, C. (2017). Characteristics of qualitative descriptive studies: A systematic review. *Research in nursing & health*, *40*(1), 23-42. https://doi.org/10.1002/nur.21768

Lukacz, P. M. (2024). Imaginaries of democratization and the value of open environmental data: Analysis of Microsoft's planetary computer. *Big Data & Society*, *11*(2), 20539517241242448. https://doi.org/10.1177/20539517241242448

Mana, A. A., Allouhi, A., Hamrani, A., Rahman, S., el Jamaoui, I., & Jayachandran, K. (2024). Sustainable AI-Based Production Agriculture: Exploring AI Applications and Implications in Agricultural Practices. *Smart Agricultural Technology*, 100416. https://doi.org/10.1016/j.atech.2024.100416

Muhie, S. H. (2022). Novel approaches and practices to sustainable agriculture. *Journal of Agriculture and Food Research*, *10*, 100446. https://doi.org/10.1016/j.jafr.2022.100446

Okot, T., & Ojok, B. (2023). Adoption of sustainable agricultural practices (SAPs): A case of coffee farmers in Eastern Uganda. *Journal of Rural and Community Development*, *18*(4).

Okot, T., Madrigal-Mendez, P., & Solorzano-Arias, D. (2023). The internet of things (IoT) for sustainability: A framework for Costa Rica. *Journal of technology management & innovation*, *18*(4), 3-17. http://dx.doi.org/10.4067/S0718-27242023000400003

Parada Gómez, Á. M., Jiménez Ureña, F. (2023). *The Competitiveness of Corn Production from a Global Value Chain Approach in the Southern Region of Costa Rica.* In: Pérez Akaki, P., Velázquez-Salazar, M., Lizama Gaitán, G.S. (eds) Global Value Chains in Latin America. Sustainable Development Goals Series. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-031-33103-9_10

Pereira, A. C., & Romero, F. (2017). A review of the meanings and the implications of the Industry 4.0 concept. *Procedia manufacturing*, *13*, 1206-1214. https://doi.org/10.1016/j.promfg.2017.09.032

Rayna, T., & Striukova, L. (2021). Involving consumers: The role of digital technologies in promoting 'prosumption' and user innovation. *Journal of the Knowledge Economy*, *12*, 218-237. https://doi.org/10.1007/s13132-016-0390-8

Shen, J., Hong, T. S., Fan, L., Zhao, R., Mohd Ariffin, M. K. A. B., & As' arry, A. B. (2024). Development of an Improved GWO Algorithm for Solving Optimal Paths in Complex Vertical Farms with Multi-Robot Multi-Tasking. *Agriculture*, *14*(8), 1372. https://doi.org/10.3390/agriculture14081372

Silva, J. C. F., Machado, K. L. D. G., Silva, A. F. D. S., Dias, R., Bodnar, V. R., Vieira, W. O., ... & Costa, L. C. D. (2025). Challenges and Opportunities for New Frontiers and Technologies to Guarantee Food Production. *Sustainability*, *17*(9), 3792. https://doi.org/10.3390/su17093792

Singh, R., & Dwivedi, G. (2025). Agri-food Supply Chain Management: A Review Using Bibliometric, Network, and Content Analyses. In *Operations Research Forum* (Vol. 6, No.

2, pp. 1-48). Springer International Publishing. https://doi.org/10.1007/s43069-025-00460-x

Taguchi, N. (2018). Description and explanation of pragmatic development: Quantitative, qualitative, and mixed methods research. *System*, *75*, 23-32. https://doi.org/10.1016/j.system.2018.03.010

Veeramanju, K. T. (2023). Revolutionizing agriculture: a case study of IBM's AI innovations. *International Journal of Applied Engineering and Management Letters (IJAEML)*, *7*(4), 95-114. https://doi.org/10.47992/IJAEML.2581.7000.0195

Wessel, L., Baiyere, A., Ologeanu-Taddei, R., Cha, J., & Blegind-Jensen, T. (2021). Unpacking the difference between digital transformation and IT-enabled organizational transformation. *Journal of the Association for information systems*, *22*(1), 102-129. https://doi.org/10.17705/1jais.00655

Zambon, I., Cecchini, M., Egidi, G., Saporito, M. G., & Colantoni, A. (2019). Revolution 4.0: Industry vs. agriculture in a future development for SMEs. *Processes*, *7*(1), 36. https://doi.org/10.3390/pr7010036

Appendix

Survey Instrument: Perceptions of AI in Sustainable Agriculture in Costa Rica

Section 1: Demographic and Organizational Information

1. What is your current professional role?
   ☐ Agricultural Engineer ☐ Agronomist ☐ Extension Officer ☐ Farm Manager ☐ Researcher ☐ Other (specify)
2. What type of organization do you work for?
   ☐ Government ☐ Private company ☐ Cooperative ☐ NGO ☐ Academic Institution ☐ Other (specify)
3. What is the size of the organization?
   ☐ Micro (1–10 employees) ☐ Small (11–50) ☐ Medium (51–250) ☐ Large (251+)
4. In which region of Costa Rica is your organization primarily located?
   ☐ Central ☐ Pacific ☐ Caribbean ☐ Northern ☐ Other (specify)
5. Do you or your organization currently use any form of artificial intelligence (AI) tools in agricultural operations?
   ☐ Yes ☐ No ☐ Not Sure

Section 2: Perceptions of AI in Agriculture

6. On a scale of 1 (Strongly Disagree) to 5 (Strongly Agree), please rate the following statements:

Statement	1	2	3	4	5
a) AI can help reduce costs in agricultural production.					
b) AI improves decision-making through data analytics.					
c) The adoption of AI enhances environmental sustainability.					
d) Farmers are open to adopting AI-based technologies.					
e) There is sufficient technical support to implement AI in the agricultural sector.					
f) The government provides adequate incentives or guidance for AI adoption in agriculture.					

Section 3: Barriers to AI Adoption

7. What are the most significant barriers to AI adoption in your context? *(Select all that apply)*
   ☐ High implementation costs
   ☐ Lack of technical knowledge
   ☐ Resistance to change among workers/farmers
   ☐ Poor data quality or access
   ☐ Lack of internet connectivity
   ☐ Legal or ethical concerns
   ☐ Unclear return on investment
   ☐ Other (specify) _____________________

Section 4: Benefits Perceived from AI Use

8. What benefits have you observed or expect from using AI in agriculture? *(Select all that apply)*
   ☐ Cost savings
   ☐ Reduced pesticide or fertilizer usage
   ☐ Increased yields
   ☐ Predictive analytics for climate or pest control
   ☐ Better resource management
   ☐ Labor savings
   ☐ Other (specify) _____________________

Section 5: Open-Ended Questions for Text Mining and Thematic Analysis

9. In your opinion, what is the biggest opportunity AI presents for sustainable agriculture in Costa Rica?
10. What do you believe are the most critical risks or ethical challenges associated with AI in agriculture?