AI-DRIVEN AGRICULTURE

AND

BLOCKCHAIN-BASED FOOD SAFETY SYSTEMS

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PREFACE

This volume brings together a collection of scholarly contributions that explore the growing role of digital technologies in transforming agriculture and food systems. As global challenges such as food security, economic sustainability, and supply chain transparency intensify, the integration of advanced technologies has become essential for improving efficiency and resilience in agribusiness.

The chapters in this book address key themes related to technological innovation and agricultural development. The examination of artificial intelligence in smart agribusiness highlights its impact on decision-making processes and gender dynamics within agricultural systems. The analysis of financial efficiency in crop production provides valuable insights into economic sustainability and farm-level performance. In addition, the exploration of blockchain technology emphasizes its potential in enhancing food safety, traceability, and trust across supply chains.

By adopting an interdisciplinary perspective, this volume integrates insights from agricultural economics, data science, and food system management. It contributes to academic discourse while also offering practical implications for researchers, policymakers, and industry professionals working to modernize agricultural systems through digital innovation.

It is hoped that this book will serve as a valuable resource for scholars and practitioners interested in agribusiness, digital transformation, and food system innovation, while encouraging further research on sustainable and technology-driven agricultural solutions.

Editorial Team
May, 2026
Türkiye

CHAPTER 1
ARTIFICIAL INTELLIGENCE AND SMART AGRIBUSINESS: GENDERED IMPLICATIONS

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INTRODUCTION

The global agricultural sector is undergoing a profound transformation driven by rapid advancements in digital technologies, particularly Artificial Intelligence (AI). This transformation often described as Agriculture 4.0 or smart agribusiness integrates AI, big data analytics, remote sensing, robotics, and Internet of Things (IoT) systems into farming and value chain operations. These innovations enable real-time decision-making, precision farming, predictive analytics, and resource optimization, thereby improving productivity, efficiency, and sustainability (Qin et al., 2025; Guo et al., 2025; Olutumise, 2026). AI-powered systems are now capable of diagnosing crop diseases, predicting weather patterns, optimizing irrigation, and facilitating market access, making them central to modern agribusiness ecosystems.

The adoption of AI in agriculture is also closely linked to global development agendas, particularly the Sustainable Development Goals (SDGs), including zero hunger (SDG 2), gender equality (SDG 5), and climate action (SDG 13). Smart agricultural technologies are widely recognized as critical tools for enhancing food security and building climate resilience, especially in regions vulnerable to environmental shocks. However, while technological innovation promises inclusive growth, emerging evidence suggests that the benefits of AI are unevenly distributed across different socio-economic groups, particularly along gender lines (Ozor et al., 2025).

Agriculture has historically been a gendered sector characterized by unequal access to resources, opportunities, and decision-making power. Women constitute nearly half of the global agricultural workforce and play crucial roles in food production, processing, and distribution, particularly in developing countries. Despite their contributions, women farmers face systemic constraints such as limited access to land ownership, credit facilities, extension services, and agricultural inputs (Dabkienė, 2025). These structural inequalities have significant implications for productivity and livelihood outcomes, as well as for the adoption of emerging technologies such as AI.

The intersection of AI and gender in agriculture introduces a new dimension to existing inequalities. On one hand, AI-driven tools offer opportunities to bridge long-standing gaps by providing women farmers with access to information, advisory services, and markets.

Digital advisory platforms, mobile-based applications, and AI-powered decision-support systems can democratize access to agricultural knowledge, thereby enhancing productivity and empowerment (Udisha & Philomina, 2024). For instance, AI-enabled mobile technologies have been shown to improve access to weather forecasts, pest management strategies, and market prices, which are critical for informed decision-making among smallholder farmers.

On the other hand, the integration of AI into agribusiness systems also risks exacerbating existing gender disparities. The digital transformation of agriculture is often accompanied by a "digital divide," which refers to unequal access to digital technologies and the skills required to use them effectively. This divide is particularly pronounced among women, especially in rural areas where access to infrastructure, education, and digital literacy remains limited (Singh et al., 2025). The gender digital divide manifests in lower rates of mobile phone ownership, internet access, and participation in digital platforms among women compared to men.

Furthermore, the design and deployment of AI systems are not inherently neutral processes. AI technologies are shaped by the data used to train them, as well as by the socio-cultural contexts in which they are developed. When datasets lack representation of women farmers or fail to capture gender-specific agricultural practices, AI systems may produce biased or irrelevant recommendations. This phenomenon, often referred to as algorithmic bias, can reinforce existing inequalities and marginalize women's knowledge and experiences in agriculture (Mugion et al., 2026). As a result, AI systems may inadvertently prioritize male-dominated farming practices or overlook the specific needs of women farmers.

In addition to issues of access and bias, the adoption of AI in agriculture has implications for labor dynamics and socio-economic structures. Automation and mechanization, driven by AI technologies, have the potential to reduce labor-intensive tasks traditionally performed by women. While this may alleviate physical burdens, it can also lead to displacement or reconfiguration of roles within agricultural systems.

Women, who are often engaged in low-skilled and informal agricultural labor, may be disproportionately affected by such changes, particularly if they lack the skills required to transition into higher-value roles within digital agribusiness systems (Carolan, 2024).

Another critical dimension of the background is the concept of intersectionality, which highlights how gender intersects with other factors such as age, education, income, and geographic location to shape access to and benefits from AI technologies. For example, young women with higher levels of education may be better positioned to adopt digital tools compared to older women with limited literacy. Similarly, women in urban or peri-urban areas may have greater access to digital infrastructure than those in remote rural regions. These intersecting factors create complex patterns of inclusion and exclusion within smart agribusiness systems (Akello & Brunori, 2025).

Recent literature also emphasizes the role of institutional and policy frameworks in shaping the adoption of AI in agriculture. Governments, development agencies, and private sector actors play a crucial role in promoting digital agriculture through investments in infrastructure, capacity building, and regulatory frameworks. However, many of these initiatives lack a gender-sensitive approach, which limits their effectiveness in addressing the specific needs and constraints of women farmers. As a result, the potential of AI to contribute to gender equality remains underutilized (Ozor et al., 2025).

In response to these challenges, there is a growing recognition of the need for gender-responsive approaches to AI in agriculture. This includes designing inclusive technologies, promoting digital literacy among women, ensuring equitable access to resources, and involving women in the development and deployment of AI systems. Such approaches are essential for harnessing the transformative potential of AI while minimizing its risks and ensuring that its benefits are equitably distributed.

Problem Statement

Despite the transformative potential of Artificial Intelligence in agriculture, significant gender disparities persist in the adoption, access, and benefits of AI-driven technologies within agribusiness systems.

These disparities are deeply rooted in structural inequalities that predate the digital revolution but are now being reshaped and, in some cases, intensified by it. The central problem addressed in this study is the unequal integration of women into AI-enabled smart agribusiness, which limits their ability to benefit from technological advancements and, in turn, undermines broader goals of inclusive agricultural development.

One of the most pressing issues is the persistent gender digital divide, which continues to hinder women's access to AI technologies. Women, particularly in rural and low-income settings, are less likely to own digital devices, access the internet, or possess the digital literacy required to utilize AI-powered tools effectively (Singh et al., 2025). This gap is not merely a technological issue but is closely linked to socio-cultural norms, educational disparities, and economic constraints that restrict women's participation in digital ecosystems. As AI becomes increasingly central to agricultural decision-making, this divide risks excluding women from critical sources of information and opportunities.

In addition to access barriers, there are significant challenges related to the design and implementation of AI systems. Many AI applications in agriculture are developed without sufficient consideration of gender-specific needs and contexts. This lack of inclusivity is reflected in datasets that underrepresent women farmers and fail to capture the diversity of agricultural practices across different gender groups. Consequently, AI systems may produce recommendations that are less relevant or effective for women, thereby reinforcing existing inequalities (Mugion et al., 2026). The absence of gender-sensitive design also limits the usability and adoption of these technologies among women farmers.

Another dimension of the problem is the unequal distribution of benefits derived from AI in agribusiness. While some farmers are able to leverage AI technologies to increase productivity, reduce costs, and access new markets, others particularly women are left behind. This disparity is exacerbated by differences in access to complementary resources such as land, credit, and extension services, which are essential for the effective use of AI tools (Dabkienė, 2025). Without these resources, even when women have access to technology, they may not be able to fully realize its benefits.

The integration of AI into agriculture also raises concerns about labor displacement and the reconfiguration of roles within agribusiness systems. Automation of tasks such as planting, harvesting, and processing may reduce the demand for manual labor, which is often performed by women. While this could potentially reduce labor burdens, it also risks marginalizing women if they are not equipped with the skills needed to participate in emerging digital roles (Carolan, 2024). This creates a paradox where technological advancement simultaneously offers opportunities for empowerment and risks of exclusion.

Furthermore, institutional and policy gaps contribute to the persistence of gender inequalities in AI-driven agriculture. Many digital agriculture initiatives are designed and implemented without adequate attention to gender considerations. This results in programs that fail to address the specific barriers faced by women or to leverage their unique contributions to agricultural systems. The lack of gender-responsive policies and frameworks limits the effectiveness of interventions aimed at promoting inclusive AI adoption (Akello & Brunori, 2025).

The problem is further compounded by the intersectionality of gender with other forms of inequality. Factors such as age, education, ethnicity, and geographic location interact with gender to shape access to and benefits from AI technologies. For example, older women or those with limited education may face additional barriers in adopting digital tools, while women in remote areas may lack access to infrastructure and support services. These intersecting inequalities create complex and layered challenges that require nuanced and context-specific solutions.

Justification of the Study

The justification for this study is grounded in the urgent need to understand and address the gendered implications of AI in agribusiness within the broader context of sustainable development. As AI continues to reshape agricultural systems, there is a critical need for research that examines not only its technical and economic impacts but also its social and gender dimensions. This study contributes to this emerging field by providing a comprehensive analysis of how AI influences gender dynamics in agribusiness and by identifying strategies for promoting inclusive and equitable outcomes.

One key justification is the recognition that gender equality is a fundamental component of sustainable agricultural development. Achieving SDG 5 (gender equality) is closely linked to progress in other areas such as food security, poverty reduction, and climate resilience. Women farmers play a vital role in agricultural production and household food security, and empowering them has been shown to have significant positive impacts on productivity and livelihoods. However, without addressing gender disparities in access to AI technologies, these benefits may not be fully realized (Ozor et al., 2025).

Another important justification is the growing influence of AI in shaping the future of agribusiness. As digital technologies become increasingly integrated into agricultural systems, they have the potential to redefine how farming is practiced, how value chains are organized, and how resources are allocated. Understanding the gendered implications of these changes is essential for ensuring that AI contributes to inclusive development rather than exacerbating inequalities. This study provides insights into the mechanisms through which AI affects gender dynamics and highlights the importance of gender-responsive approaches.

The study is also justified by the need to address the digital gender divide, which remains a significant barrier to inclusive development. Despite advances in technology, many women—particularly in rural areas—continue to face challenges in accessing and using digital tools. This divide not only limits their participation in digital economies but also restricts their ability to benefit from innovations in agriculture. By examining the factors contributing to this divide and identifying strategies for bridging it, this study contributes to efforts to promote digital inclusion (Singh et al., 2025).

Furthermore, the study addresses gaps in existing literature by integrating perspectives from multiple disciplines, including agriculture, information technology, gender studies, and development studies. While there is a growing body of research on AI in agriculture and on gender in agriculture, relatively few studies have examined the intersection of these fields in a comprehensive manner. This study fills this gap by synthesizing recent literature and providing a holistic analysis of the gendered implications of AI in agribusiness.

The practical relevance of this study is another important justification. Policymakers, development practitioners, and private sector actors are increasingly investing in digital agriculture initiatives, but many lack the tools and frameworks needed to ensure that these initiatives are inclusive and gender-responsive. By providing evidence-based recommendations and policy insights, this study supports the design and implementation of interventions that promote equitable access to and benefits from AI technologies.

Finally, the study is justified by its potential to inform future research and practice. As AI continues to evolve, new challenges and opportunities will emerge, requiring ongoing analysis and adaptation. This study lays the groundwork for future research by identifying key issues and areas for further investigation, including the role of participatory design, the impact of AI on labor dynamics, and the importance of intersectional approaches to inclusion.

In conclusion, this study is justified by its contribution to understanding the complex and evolving relationship between AI, agribusiness, and gender. By addressing critical gaps in knowledge and providing actionable insights, it supports efforts to harness the transformative potential of AI while promoting gender equality and inclusive development.

Research Objectives

- To examine the role of AI in transforming agribusiness systems
- To analyze gender disparities in access to AI-driven agricultural technologies
- To evaluate the implications of AI adoption on women farmers
- To propose frameworks for gender-inclusive smart agribusiness

1. LITERATURE REVIEW

Theoretical Framework

The theoretical framework for this study is grounded in an interdisciplinary synthesis of perspectives that explain the interaction between technology, gender, and agribusiness systems. Understanding the gendered implications of Artificial Intelligence (AI) in agriculture requires moving beyond purely technological explanations and engaging with social theories that account for power relations, access to resources, and structural inequalities.

This study draws primarily on Feminist Technology Theory, Digital Divide Theory, the Sustainable Livelihoods Framework, and complementary perspectives such as Intersectionality Theory and Innovation Systems Theory. Together, these frameworks provide a comprehensive lens through which to analyze how AI-driven transformations in agribusiness shape—and are shaped by gender dynamics.

Feminist Technology Theory provides a foundational perspective for understanding the relationship between gender and technological development. This theory challenges the notion that technology is neutral, arguing instead that it is socially constructed and embedded within existing power relations. In the context of AI and agriculture, Feminist Technology Theory highlights how technological systems often reflect the biases, assumptions, and priorities of their designers, who are frequently male and based in technologically advanced contexts. As a result, AI tools may fail to adequately capture the realities and needs of women farmers, particularly in developing regions (Ozor et al., 2025). For example, data used to train AI systems may underrepresent women's agricultural activities, leading to recommendations that are less relevant or effective for them. This aligns with findings by Mugion et al. (2026), who emphasize that Agriculture 4.0 technologies often overlook women's roles due to gender gaps in data representation and participation.

Furthermore, Feminist Technology Theory underscores the importance of inclusivity in the design and deployment of technological systems. It advocates for participatory approaches that involve women and other marginalized groups in the development process, thereby ensuring that technologies are responsive to diverse needs and contexts. Recent studies emphasize that integrating feminist epistemologies into AI development can enhance equity and effectiveness, particularly in sectors such as agriculture where gender disparities are pronounced (Okongo & Okaka, 2025). This perspective is critical for addressing algorithmic bias and ensuring that AI systems contribute to gender equality rather than reinforcing existing inequalities.

Closely related to this is the concept of feminist political economy, which examines how economic systems and technological innovations interact with gendered labor dynamics.

In agribusiness, AI-driven automation and digitalization can reshape labor markets by reducing demand for manual labor while increasing demand for technical skills. Feminist analyses suggest that such transformations may disproportionately disadvantage women, who are often concentrated in low-skilled and informal agricultural roles (Joanita, 2025). At the same time, these changes may create new opportunities for women to engage in higher-value activities, provided that they have access to education, training, and resources. This duality highlights the need for gender-responsive policies that support women's transition into digital agribusiness roles.

Digital Divide Theory is another critical framework for understanding gender disparities in AI adoption within agriculture. This theory examines inequalities in access to digital technologies, skills, and infrastructure, which are essential for participating in the digital economy. The digital divide is not merely a matter of physical access to devices or connectivity but also encompasses disparities in digital literacy, affordability, and cultural acceptance (Singh et al., 2025). In the context of smart agribusiness, the gender digital divide manifests in lower rates of mobile phone ownership, internet usage, and participation in digital platforms among women compared to men.

Recent research highlights that the digital divide in agriculture is multidimensional, encompassing not only access but also the ability to effectively use and benefit from digital technologies. For instance, even when women have access to mobile devices, they may face barriers such as limited digital skills, lack of relevant content, and socio-cultural restrictions on technology use (Sarku & Kranjac-Berisavljevic, 2025). These challenges are further compounded by rural-urban disparities and socio-economic inequalities, creating a "triple divide" that disproportionately affects women farmers. According to Singh et al. (2025), addressing the gender digital divide requires a holistic approach that includes infrastructure development, capacity building, and gender-sensitive policy interventions.

The relevance of Digital Divide Theory to this study lies in its ability to explain why the benefits of AI in agriculture are unevenly distributed. While AI technologies have the potential to enhance productivity and efficiency, their impact is contingent upon users' ability to access and utilize them effectively.

Without addressing underlying digital inequalities, the adoption of AI may exacerbate existing disparities, leaving women farmers further marginalized. This underscores the importance of designing inclusive digital ecosystems that enable equitable participation in smart agribusiness systems.

The Sustainable Livelihoods Framework (SLF) provides another important theoretical lens for this study. The SLF focuses on how individuals and households utilize various assets—human, social, natural, physical, and financial to achieve sustainable livelihoods. In the context of agriculture, these assets determine farmers' capacity to adopt new technologies, respond to shocks, and improve their well-being. AI technologies can enhance these assets by providing access to information, improving resource management, and facilitating market linkages (Azumah et al., 2023).

However, access to livelihood assets is often gendered, with women facing significant constraints in accessing land, credit, education, and extension services. These constraints limit their ability to adopt and benefit from AI technologies, even when such technologies are available. For example, a woman farmer who lacks access to credit may be unable to invest in digital tools or complementary inputs required for precision agriculture. Similarly, limited access to education and training can hinder women's ability to use AI-driven systems effectively. As noted by Das et al. (2026), bridging the gender gap in digital agriculture requires strengthening women's access to livelihood assets and integrating gender considerations into development interventions.

The SLF also emphasizes the role of vulnerability contexts, such as climate change, economic instability, and social inequalities, in shaping livelihood outcomes. AI technologies have the potential to enhance resilience by providing tools for climate adaptation and risk management. However, their effectiveness depends on equitable access and inclusion. Without addressing gender disparities, AI-driven solutions may fail to reach the most vulnerable populations, thereby limiting their impact on sustainable development.

Intersectionality Theory further enriches the theoretical framework by highlighting the interconnected nature of social identities and inequalities. This theory posits that gender does not operate in isolation but intersects with other factors such as age, education, ethnicity, and geographic location to shape individuals' experiences and opportunities.

In the context of AI and agribusiness, intersectionality helps explain why some women are able to adopt and benefit from digital technologies while others are excluded (Mensah & van Wynsberghe, 2025).

For instance, younger women with higher levels of education and access to urban infrastructure may be more likely to engage with AI-driven agricultural tools than older women in remote rural areas. Similarly, women from marginalized ethnic groups may face additional barriers due to discrimination and limited access to resources. Intersectionality thus provides a nuanced understanding of gender disparities in smart agribusiness, emphasizing the need for context-specific and inclusive approaches to technology development and deployment.

Another relevant perspective is Innovation Systems Theory, which examines how interactions among various actors—such as farmers, researchers, policymakers, and private sector organizations—shape the development and diffusion of innovations. In the context of AI in agriculture, innovation systems include digital platforms, research institutions, extension services, and market actors that collectively influence technology adoption. This theory highlights the importance of institutional frameworks, knowledge flows, and collaborative networks in promoting inclusive innovation (Anim et al., 2025).

From a gender perspective, Innovation Systems Theory underscores the need to ensure that women are actively included in innovation processes. This includes involving women farmers in the design and testing of AI technologies, as well as ensuring that extension services and training programs are accessible and responsive to their needs. Studies have shown that gender-inclusive innovation systems are more effective in promoting adoption and achieving equitable outcomes (Sheikh & Berenyi, 2024). By fostering collaboration and inclusivity, innovation systems can help bridge gender gaps and enhance the impact of AI in agribusiness.

In addition to these frameworks, the concept of “recognition justice” has emerged as a critical lens for analyzing digital agriculture. Recognition justice focuses on the acknowledgment and valuation of diverse knowledge systems, identities, and contributions within socio-technical systems.

In the context of AI, this involves recognizing the knowledge and practices of women farmers, which are often overlooked in formal data systems and technological designs (Carolan, 2024). Failure to recognize these contributions can lead to the marginalization of women's roles and the development of technologies that are not aligned with their needs.

Recognition justice also emphasizes the importance of addressing power imbalances in the production and use of knowledge. In many cases, AI technologies are developed by actors in the Global North and deployed in the Global South, raising concerns about epistemic inequality and the imposition of external knowledge systems. Incorporating local and gendered knowledge into AI development is therefore essential for ensuring relevance, effectiveness, and equity.

Collectively, these theoretical perspectives provide a comprehensive framework for analyzing the gendered implications of AI in smart agribusiness. Feminist Technology Theory highlights the social construction of technology and the need for inclusive design; Digital Divide Theory explains disparities in access and usage; the Sustainable Livelihoods Framework emphasizes the role of assets and vulnerabilities; Intersectionality Theory provides a nuanced understanding of inequality; and Innovation Systems Theory underscores the importance of institutional and collaborative processes. Together, these frameworks reveal that the impact of AI on gender equality in agriculture is not predetermined but is shaped by complex interactions among technological, social, economic, and institutional factors.

In conclusion, the theoretical framework underscores the importance of adopting a holistic and interdisciplinary approach to studying AI in agribusiness. It highlights that achieving gender equality in the context of digital transformation requires not only technological innovation but also social, institutional, and policy interventions. By integrating these theoretical perspectives, this study provides a robust foundation for analyzing the opportunities and challenges associated with AI-driven smart agribusiness and for developing strategies to promote inclusive and equitable outcomes.

Conceptual Framework

The conceptual framework for this study illustrates the dynamic relationships between Artificial Intelligence (AI) technologies and gendered outcomes within smart agribusiness systems. At its core, the framework positions AI technologies—including precision agriculture, machine learning, and digital advisory platforms—as the primary independent variable driving transformation in agribusiness. These technologies influence farming practices, decision-making processes, and value chain participation. However, their impact is not direct or uniform; rather, it is shaped by a set of interacting socio-economic and institutional factors.

Central to the framework are gender dynamics, which mediate how men and women access, adopt, and benefit from AI innovations. These dynamics are influenced by access to resources such as land, credit, education, and training, as well as socio-cultural factors including norms, roles, and power relations. Women farmers often face structural barriers in these areas, limiting their engagement with AI-enabled systems. As a result, even when technologies are available, gender inequalities can constrain their effective utilization.

The framework further identifies key mediating variables, including digital literacy, AI usability and design, extension services, and institutional support. Digital literacy determines the ability of farmers—particularly women—to interact with AI tools, while user-centered design influences the accessibility and relevance of these technologies. Extension services and policy institutions play a critical role in facilitating knowledge transfer, capacity building, and inclusive implementation. These mediating processes collectively determine whether AI adoption leads to equitable outcomes.

Finally, the framework highlights outcomes such as productivity, income generation, empowerment, and social inclusion. When gender-sensitive conditions are met, AI can enhance women's access to markets, improve decision-making power, and promote equitable participation in agribusiness. Conversely, weak mediation may reinforce disparities, leading to unequal benefits. Thus, the framework underscores that gender-responsive interventions are essential for ensuring that AI-driven agribusiness contributes to inclusive and sustainable development.

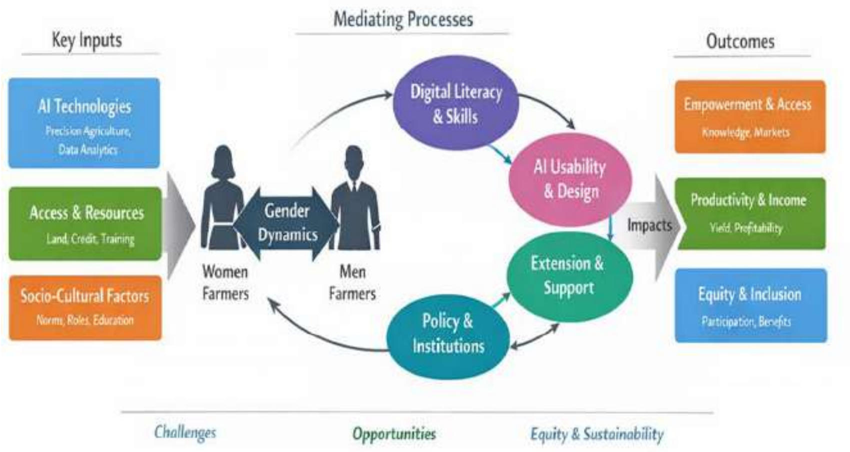

Figure 1. Conceptual framework

2. RESEARCH METHODOLOGY

This study adopts a systematic literature review methodology, which is widely used in examining emerging interdisciplinary fields such as Artificial Intelligence (AI) in agriculture and gender studies. A systematic approach enables the identification, evaluation, and synthesis of existing scholarly evidence in a transparent and replicable manner. Recent studies emphasize that systematic reviews are particularly appropriate for digital agriculture research due to the rapid evolution of technologies and the need to consolidate fragmented knowledge across disciplines (Aroba & Rudolph, 2024; Sun et al., 2026). This method ensures that the analysis captures both technological developments and socio-economic dimensions, including gendered implications.

The data collection process involved a comprehensive search of peer-reviewed literature from major academic databases, including Scopus, Web of Science, ScienceDirect, and Google Scholar. The search focused on publications between 2023 and 2026 to ensure relevance and currency. Keywords such as "Artificial Intelligence in agriculture," "smart agribusiness," "gender and digital agriculture," "AI adoption," and "gender digital divide" were used in various combinations.

Boolean operators (AND, OR) were applied to refine search results and improve accuracy. This approach aligns with established systematic review protocols in digital agriculture studies (Islam et al., 2024).

To ensure rigor, inclusion and exclusion criteria were applied. Included studies were those that (i) focused on AI or digital technologies in agriculture, (ii) addressed gender dimensions or social inclusion, and (iii) were empirical or theoretical peer-reviewed works. Excluded materials included non-academic sources, opinion pieces without empirical grounding, and studies published before 2023 unless they provided foundational insights. This filtering process enhances the reliability and academic integrity of the review (Sarku & Kranjac-Berisavljevic, 2025).

Following data collection, the study employed thematic analysis to synthesize findings. This involved coding and categorizing data into key themes such as access to technology, digital literacy, gender disparities, AI adoption, and socio-economic outcomes. Thematic analysis is particularly suitable for qualitative synthesis, as it allows for the identification of patterns and relationships across diverse studies (Ozor et al., 2025). The process included data familiarization, generation of initial codes, theme development, and interpretation, ensuring a structured and systematic analysis.

To enhance validity, the study also incorporated elements of bibliometric and comparative analysis, examining publication trends, regional focus, and methodological approaches within the literature. This helps contextualize findings and identify research gaps, particularly in relation to gender-responsive AI in agribusiness (Mugion et al., 2026). Overall, the methodology provides a robust framework for analyzing the complex and evolving intersection of AI, agriculture, and gender, ensuring that conclusions are grounded in credible and up-to-date scholarly evidence.

3. RESULTS AND DISCUSSION

The analysis of recent literature reveals that the integration of Artificial Intelligence (AI) into agribusiness systems has generated significant transformations across agricultural production, value chains, and rural livelihoods. However, these transformations are neither uniform nor equitable.

The results indicate that while AI technologies have enhanced efficiency, productivity, and decision-making in agriculture, their adoption and benefits are strongly mediated by gendered structures. This section presents a detailed discussion of key findings, organized around major thematic areas including access and adoption, digital gender divide, productivity and economic outcomes, empowerment and decision-making, labor dynamics, algorithmic bias, institutional influences, and intersectional inequalities.

One of the most prominent findings across the reviewed literature is the uneven access to and adoption of AI technologies among farmers, particularly along gender lines. AI-driven tools such as precision agriculture systems, mobile-based advisory platforms, and predictive analytics applications have been widely promoted as solutions to improve agricultural productivity and resilience. However, evidence consistently shows that men are more likely to adopt these technologies than women. This disparity is largely attributed to differences in access to resources, education, and information. Women farmers often face constraints in accessing extension services, training programs, and financial capital required to adopt AI technologies (Ozor et al., 2025). As a result, even when AI tools are available within a community, women's uptake remains significantly lower.

Closely linked to this is the persistent digital gender divide, which emerges as a central barrier to inclusive AI adoption in agriculture. The digital divide encompasses disparities in access to digital devices, internet connectivity, and digital literacy. Studies indicate that women in rural areas are less likely to own smartphones, have access to the internet, or possess the technical skills needed to use AI-enabled platforms effectively (Singh et al., 2025). This gap is further exacerbated by socio-cultural norms that restrict women's use of technology or prioritize men's access to household digital resources. Consequently, the benefits of AI-driven agricultural innovations are disproportionately captured by male farmers, reinforcing existing inequalities.

In addition to access issues, the usability and design of AI technologies play a critical role in shaping adoption patterns. Many AI systems are developed without adequate consideration of the specific needs and contexts of women farmers. For example, digital advisory platforms may be designed in languages or formats that are not accessible to women with limited literacy.

Similarly, the timing and mode of information delivery may not align with women's daily schedules and responsibilities. These design limitations reduce the relevance and usability of AI tools for women, further limiting their adoption (Mugion et al., 2026). The findings suggest that user-centered and gender-responsive design approaches are essential for improving accessibility and effectiveness.

The results also highlight significant impacts of AI on agricultural productivity and economic outcomes, with important gendered implications. AI technologies have been shown to improve crop yields, optimize resource use, and enhance market access through data-driven decision-making. For farmers who are able to adopt these technologies, the economic benefits can be substantial, including increased income and reduced production costs (Olutumise, 2026). However, because women are less likely to adopt AI tools, they are also less likely to benefit from these productivity gains. This creates a widening gap in economic outcomes between male and female farmers, with potential long-term implications for rural inequality and poverty.

At the same time, some studies suggest that AI has the potential to empower women farmers by providing access to information and services that were previously unavailable. For instance, mobile-based AI applications can deliver real-time information on weather conditions, pest management, and market prices, enabling women to make more informed decisions. In contexts where women have limited access to traditional extension services, these digital platforms can serve as alternative sources of knowledge and support (Udisha & Philomina, 2024). Moreover, AI-driven financial technologies, such as digital credit scoring systems, can improve women's access to financial services by reducing reliance on collateral and formal documentation.

Despite these positive outcomes, the extent to which AI contributes to women's empowerment and decision-making power remains mixed. Empowerment is a multidimensional concept that includes economic, social, and political dimensions. While access to AI technologies can enhance women's knowledge and skills, it does not automatically translate into greater decision-making authority within households or communities. In many cases, entrenched gender norms continue to limit women's control over resources and their participation in decision-making processes (Foster et al., 2023).

For example, even when women use digital tools to access market information, decisions regarding the sale of produce or allocation of income may still be controlled by male household members.

Another critical area of discussion is the impact of AI on labor dynamics and employment in agriculture. AI-driven automation and mechanization have the potential to reduce labor-intensive tasks, such as planting, weeding, and harvesting. While this can alleviate physical burdens, particularly for women who often perform manual labor, it also raises concerns about job displacement. Women, who are disproportionately represented in low-skilled and informal agricultural roles, may be more vulnerable to displacement as these tasks become automated (Carolan, 2024). Furthermore, the shift toward digital agriculture creates demand for new skills, such as data analysis and technology management, which women may be less likely to possess due to educational and training disparities.

The findings also point to the issue of algorithmic bias and data inequality in AI systems. AI technologies rely on large datasets to generate predictions and recommendations. However, if these datasets do not adequately represent the experiences and practices of women farmers, the resulting algorithms may produce biased outputs. For example, crop management recommendations based on data from male-dominated farming systems may not be applicable to women's farming practices, which often differ in terms of scale, crop types, and resource availability (Mugion et al., 2026). This can lead to suboptimal outcomes and further marginalize women within digital agricultural systems.

Institutional and policy factors play a crucial role in shaping the gendered impacts of AI in agribusiness. The results indicate that many digital agriculture initiatives lack a gender-sensitive approach, limiting their effectiveness in addressing women's needs. For instance, training programs and extension services are often designed without considering gender-specific constraints, such as time availability, mobility restrictions, and caregiving responsibilities. Additionally, policies related to digital infrastructure, data governance, and agricultural innovation often do not explicitly address gender equality (Akello & Brunori, 2025). This institutional gap hinders the development of inclusive AI ecosystems and reinforces existing disparities.

Another important finding is the role of private sector actors and digital platforms in shaping access to AI technologies. Agritech companies and digital service providers are increasingly influential in the development and dissemination of AI tools. While these actors can drive innovation and scalability, their business models may prioritize profitability over inclusivity. As a result, services may be designed for commercially viable segments, often excluding smallholder farmers and women who have limited purchasing power (Rotz et al., 2019). This raises concerns about the commercialization of digital agriculture and its implications for equity and access.

The discussion also highlights the importance of intersectionality in understanding gendered outcomes. Gender does not operate in isolation but intersects with other factors such as age, education, income, and geographic location. For example, younger women with higher levels of education may be more likely to adopt AI technologies compared to older women with limited literacy. Similarly, women in urban or peri-urban areas may have better access to digital infrastructure than those in remote rural regions (Mensah & van Wynsberghe, 2025). These intersecting factors create diverse experiences and outcomes, underscoring the need for context-specific approaches to promoting inclusive AI adoption.

In examining regional variations, the results indicate that the gendered impacts of AI in agriculture differ across contexts. In regions with relatively higher levels of digital infrastructure and gender equality, such as parts of Asia and Latin America, women are more likely to engage with AI technologies and benefit from their use. In contrast, in regions with significant gender disparities and limited infrastructure, such as Sub-Saharan Africa, the challenges are more pronounced (Ozor et al., 2025). These regional differences highlight the importance of tailoring interventions to local contexts and addressing structural barriers at multiple levels.

The role of education and capacity building emerges as a critical factor in enabling women's participation in AI-driven agribusiness. Training programs that focus on digital literacy, technical skills, and entrepreneurship can enhance women's ability to adopt and benefit from AI technologies. However, the effectiveness of such programs depends on their accessibility and relevance.

Studies suggest that gender-sensitive training approaches, which consider women's specific needs and constraints, are more effective in promoting adoption and empowerment (Das et al., 2026). This includes flexible training schedules, local language content, and participatory learning methods.

Another significant theme is the potential of AI to contribute to climate resilience and sustainability, with important gender implications. AI technologies can support climate-smart agriculture by providing tools for weather forecasting, risk assessment, and resource management. These capabilities are particularly valuable for women farmers, who are often more vulnerable to climate-related shocks due to limited access to resources (Anim et al., 2025). However, as with other benefits, the extent to which women can leverage these tools depends on their access to and ability to use AI technologies.

The findings also emphasize the importance of participatory approaches and co-design in developing inclusive AI solutions. Involving women farmers in the design and testing of AI technologies can help ensure that these tools are relevant, accessible, and responsive to their needs. Participatory approaches also empower women by giving them a voice in the innovation process and recognizing their knowledge and expertise (Okongo & Okaka, 2025). This aligns with broader calls for inclusive innovation systems that prioritize equity and social justice.

Finally, the discussion highlights the need for integrated and multi-stakeholder approaches to addressing gender disparities in AI-driven agribusiness. Governments, development agencies, private sector actors, and civil society organizations all have a role to play in promoting inclusive digital agriculture. This includes investing in infrastructure, developing gender-responsive policies, supporting capacity building, and fostering collaboration among stakeholders. Without coordinated efforts, the potential of AI to contribute to gender equality and sustainable development may remain unrealized.

CONCLUSION

The integration of Artificial Intelligence (AI) into agribusiness represents a transformative shift with far-reaching implications for productivity, sustainability, and rural development. This review demonstrates that while AI-driven technologies offer significant opportunities to enhance agricultural efficiency and resilience, their benefits are not equitably distributed. Gender disparities remain a critical challenge, with women farmers facing structural barriers in access to digital tools, resources, and decision-making platforms. These inequalities are rooted in longstanding socio-economic and cultural constraints, which are now being reshaped within digital agricultural systems.

The findings underscore that AI is not inherently inclusive; rather, its impact depends on the context in which it is developed and deployed. Without deliberate gender-responsive strategies, AI risks reinforcing existing inequalities through digital exclusion, algorithmic bias, and unequal access to benefits. However, when designed and implemented inclusively, AI has the potential to empower women by improving access to information, enhancing productivity, and strengthening participation in agribusiness value chains. Therefore, achieving equitable outcomes requires integrating gender considerations into all stages of AI development and adoption.

Recommendations

To address the identified challenges, several strategic recommendations are proposed. First, there is a need to promote gender-responsive design of AI technologies, ensuring that tools are accessible, user-friendly, and tailored to the specific needs of women farmers. This includes incorporating local languages, simplifying interfaces, and aligning technological solutions with women's daily realities.

Second, capacity building and digital literacy programs should be prioritized to enhance women's ability to effectively use AI tools. Training initiatives must be inclusive, context-specific, and sensitive to socio-cultural constraints, enabling women to participate actively in digital agribusiness.

Third, improving access to resources, including finance, land, and infrastructure, is essential for enabling women to adopt AI technologies.

Innovative financial mechanisms, such as digital credit systems, can help overcome traditional barriers to resource access.

Fourth, promoting participatory approaches in the development and deployment of AI systems is critical. Involving women farmers in co-design processes ensures that technologies are relevant, inclusive, and responsive to their needs.

Finally, strengthening multi-stakeholder collaboration among governments, private sector actors, and development organizations can facilitate the creation of inclusive digital ecosystems that support equitable AI adoption.

Policy Implications

The findings of this study have significant implications for policy development and implementation. Governments should integrate gender considerations into national digital agriculture strategies, ensuring that policies explicitly address the needs and constraints of women farmers. This includes investing in rural digital infrastructure, expanding internet access, and promoting affordable technologies.

Additionally, policymakers must develop regulatory frameworks that address algorithmic bias and data inclusivity, ensuring that AI systems are fair, transparent, and representative of diverse user groups. Gender-disaggregated data collection should be prioritized to improve the accuracy and relevance of AI-driven solutions.

There is also a need for inclusive extension services and support systems that leverage both traditional and digital channels to reach women farmers effectively. Public policies should incentivize private sector actors to adopt inclusive business models that prioritize accessibility and equity.

Ultimately, achieving gender-inclusive smart agribusiness requires a holistic policy approach that combines technological innovation with social and institutional reforms. By aligning AI development with gender equality goals, policymakers can ensure that digital transformation contributes to sustainable and inclusive agricultural development.

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CHAPTER 2
FINANCIAL EFFICIENCY ANALYSIS OF WHITE RADISH (*RAPHANUS SATIVUS L.)* FARMING IN MEKONG DELTA VIETNAM

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INTRODUCTION

The Mekong Delta is strategically transitioning toward high-productivity, high-quality, and high-value agriculture. Situated in the central lower reaches of the Mekong River, some provinces have seen white radish (*Raphanus sativus L.)* emerge as a pivotal crop, significantly enhancing economic returns and stabilizing smallholder livelihoods. Often referred to as 'white ginseng' due to its high nutritional profile, white radish is primarily cultivated in some provinces.

Despite this growth, the white radish sub-sector faces multifaceted challenges. Escalating input costs, coupled with frequent pest and disease outbreaks, have compromised product quality and driven up expenditure on chemical interventions. Furthermore, the sector is increasingly vulnerable to climate-induced weather fluctuations. Production remains fragmented at the household scale, characterized by a lack of vertical and horizontal linkages, which leads to inefficiencies in market distribution. Significant price volatility and yield fluctuations have occasionally resulted in substantial financial losses for farmers. Therefore, this study is essential to provide a comprehensive assessment of the current production status and economic efficiency of this model. The findings aim to propose strategic solutions for optimizing production-consumption linkages, enhancing household income, and fostering a sustainable brand for white radish within the framework of rural economic transformation. Thus, this study aims to assess the current state of white radish cultivation by farming households, analyze the financial efficiency of white radish farming households, analyze the factors affecting the profitability of white radish farming households, and propose solutions to improve the financial efficiency and sales of white radish farming households in the research area.

1. LITERATURE REVIEW AND RESEARCH METHODOLOGY

1.1 Literature Review

Previous literature has extensively utilized descriptive statistics to evaluate the socio-economic characteristics and production status of smallholders, as exemplified by the studies of Ha Vu Son (2014).

Nguyen Tien Dung and Le Khuong Ninh (2015), and Nguyen Tuan Kiet (2017). To quantify production outcomes and financial performance, standard economic indicators including total revenue, production costs, and net profit are typically employed. Furthermore, financial efficiency is assessed through key ratios such as revenue-to-cost, profit-to-cost, and profit-to-revenue (Nguyen Tien Dung and Le Khuong Ninh, 2015; Nguyen Tuan Kiet, 2017).

Beyond descriptive analysis, multiple linear regression models have been widely adopted to examine the determinants and magnitude of impact regarding productivity, output, and profitability at the farm level (Nguyen and Duong, 2020; Pham and Pham, 2020). Alternatively, binary logistic regression has been utilized to identify factors influencing the transition between different farming models (Ngo and Duong, 2018). While various analytical frameworks exist for assessing financial efficiency, the selection of specific econometric tools remains highly context-dependent, reflecting the distinct advantages and limitations of each approach.

Complementing these quantitative methods, several scholars (e.g., Ngo and Duong, 2018; Nguyen and Duong, 2016; Pham and Pham, 2020) have integrated SWOT analysis to evaluate resources for household economic development. This framework facilitates a comprehensive appraisal of internal factors (Strengths and Weaknesses) alongside external influences (Opportunities and Threats). By systematically identifying these factors, researchers can formulate strategic solutions that leverage existing advantages while mitigating inherent challenges to foster sustainable agricultural development

Extensive research has investigated the determinants of profitability across various agricultural models. In the context of chive cultivation, Tran Thi Kim Chau (2020) identified that expenditures on fertilizers, pesticides, electricity, harvesting, and both family and hired labor are critical factors. Similarly, Nguyen (2017) conducted a comparative analysis between rice-producing households participating in the 'Large-Scale Field' program and independent farmers, finding that profitability was significantly influenced by fertilizer and pesticide costs, technical training, skill levels, cultivated area, and experience.

Further empirical evidence from Le and Le (2013) highlights that the household head's expertise, the adoption of advanced agricultural technologies, farming experience, and market prices exhibit a positive correlation with net returns. Conversely, rising unit prices for seeds, labor, DAP fertilizers, and pesticides were found to exert downward pressure on the profit margins of purple onion growers. These findings are echoed in the work of Nguyen Trung Phong (2020), who noted that profitability in rice production is contingent upon the chosen cultivation model, access to training, the age of the household head, family labor availability, and the frequency of market information seeking.

In other sub-sectors such as sugarcane and corn, studies by Phan and Mai (2015) and Le and Vo (2017) emphasized that profit fluctuates based on selling prices, economies of scale (cultivated area), labor costs, and the intensity of fertilizer and pesticide application. Additionally, mechanization and technical proficiency were cited as vital drivers of efficiency. Specifically regarding perennial crops, Nguyen Thi Thu An (2017) demonstrated that specialized experience in mandarin orange cultivation enables farmers to effectively manage pests and optimize planting density, thereby enhancing yield and profitability.

Synthesizing these findings, scholars consistently advocate for integrated strategic solutions to improve financial performance. Key recommendations include enhancing technical capacity through training and knowledge-exchange programs to minimize production costs and mitigate risks. Moreover, there is a strong consensus on the necessity for smallholders to transition toward collective economy models—such as cooperatives and agribusiness linkages—and to adopt rigorous quality standards like VietGAP and GlobalGAP to strengthen market competitiveness

1.2 Data Collection and Analysis Methodology

1.2.1 Data Collection Method

Primary data for this research were collected using a convenience sampling technique. Structured questionnaires were developed and administered through face-to-face interviews with 60 white radish-producing households in the Mekong Delta.

The survey instrument was designed to capture comprehensive data, including: (i) socio-economic profiles of the households (e.g., age, formal education, farming experience, and household demographics); (ii) production metrics such as yield and output; (iii) market engagement and consumption patterns; and (iv) an assessment of the perceived advantages and operational constraints encountered during the production process within the study area.

1.2.2 Research Methodology

Descriptive Statistical Method

Descriptive statistical methods involve collecting data, summarizing, presenting, calculating, and describing various characteristics to generally reflect the research subject. This study applies this method to clearly show the characteristics of white radish farming households, reflecting factors related to the process of growing and consuming white radish. For example: the number of seeds, the amount of fertilizer and pesticides, the area of white radish cultivation, yield, productivity, and price of white radish, etc.

Analysis of Financial Indicators

From the collected results, the financial efficiency of white radish farming households is analyzed through the following indicators:

Productivity: is the output or quantity of products produced per unit area per crop season or per year.

$$\text{Productivity} = \text{Output} / \text{Unit Area};$$

Revenue: is the total amount of money received from the sale of products, provision of services, financial activities, and other activities. In other words, revenue is the total value of the product per unit area.

$$\text{Revenue} = \text{Selling Price} * \text{Output};$$

Total Costs: is the total amount of money that the producer spends on production activities from the production stage to the final product stage.

Total Costs = Labor Costs + Material Costs + Other Costs;

Profit: is the difference between revenue and production costs, or in other words, profit is the remaining income of the farmer after deducting the costs incurred during the production process.

Profit = Total Revenue – Total Costs;

Income: is the difference between total revenue and total costs (excluding family labor).

Income = Total Revenue – Total Costs (excluding family labor);

Profit margin on total costs: indicates what percentage of production costs is profit. This figure assesses the profitability of investment costs per unit of land.

Profit margin on total costs = Profit / Total costs;

Revenue to Total Cost: This ratio is calculated by dividing total revenue by total production costs (excluding family labor costs). This ratio indicates how much revenue is generated for every dollar of production cost spent.

Revenue to Total Cost = Revenue / Total Cost;

Profit to Revenue: This reflects how much profit a farmer earns for every dollar of revenue spent. It means they retain a percentage of the value of production generated. This is the profit margin.

Profit to Revenue = Profit / Revenue.

Multiple Regression Model

This study uses the multivariate regression model analysis method to analyze the factors affecting the profit of white radish farmers.

The purpose of this method is to predict or estimate the value of a variable (called the predictor or dependent variable) in relation to the values of one or more other variables (called the predictor variables, independent variables, or descriptive variables).

The multiple regression model has the following form:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5 + \beta 6X6 + e$$

Where Y is the dependent variable: Profit of the farming household (1,000 VND/1,000 m2)

β0: Constant number of variables, β1, β2, β3,…,β6: are regression coefficients. These coefficients indicate the degree of influence of each independent variable on the average value of the dependent variable when the remaining variables are fixed. These coefficients also indicate how many units the average of Y will change (increase or decrease) when variables X1, X2,…,X6 increase (or decrease) by 1 unit, provided that other variables remain constant. X1, X2, X3,…,X6 are independent variables.

Synthesizing previous studies, this research presents factors that may affect the profitability of the white radish farming model of farming households in Mekong Delta Vietnam.

2. RESULTS AND DISCUSSION

2.1 Description of Sample Data and Results of Descriptive Statistical Analysis

The average age of the farming households is around 47 years old, with the youngest household being 27 years old and the oldest 67 years old. Those directly involved in cultivation are relatively old because most young people work in large cities such as Ho Chi Minh City and Can Tho. Furthermore, research area has the large industrial park, so young people of working age prefer working in industrial parks rather than farming. This is understandable, as industrial workers generally offer more stable and higher incomes than agricultural activities in rural areas. The analysis shows that the minimum number of years of experience is 1 year and the maximum is 20 years.

The average number of years of experience in growing white radishes among the farming households is 8 years. The group with 5 to 15 years of experience accounts for the majority (78.3%), equivalent to 47 farming households. According to field surveys, although the cultivation of white radish in Mang Thít district has only recently begun to flourish, it has a long history, resulting in a high level of experience among farmers.

Furthermore, the number of farmers participating in cooperatives in the area is very low, with only 4 households (7%), while 93% (56 households) do not participate. Most of the cultivation techniques used in growing white radish are accumulated from the valuable experience of previous generations.

Participating in cooperatives offers many benefits to farmers, such as support with seeds, organic fertilizers, funding for technology transfer, knowledge of seed selection, and methods of caring for white radishes at different stages of growth and development to achieve high yields. Simultaneously, farmers learn how to identify, prevent, and treat common diseases affecting white radishes. Some cooperatives are taking advantage of government support to invest in additional machinery and equipment to improve productivity and operational efficiency, expand into new industries, develop new models, and strengthen consumption linkages to guarantee the purchase of agricultural products from members. Although local cooperatives have implemented the VietGAP model, they still do not provide enough organic fertilizer, leading to substandard product quality and consequently lower-than-expected prices. This makes people hesitant to participate in cooperatives and the VietGAP model.

Furthermore, 56 households (93%) did not participate in the training, and only 4 households (7%) did. However, those who did participate had been attending for a very long time with very few training sessions. The techniques used by these farmers to grow white radishes are mainly based on their own experience accumulated over the years, following family traditions or learning from neighboring farmers. In addition, there are many limitations in the organization of the training, such as the infrequent number of sessions; insufficient and uneven dissemination of information; some households in remote hamlets and communes lacking information; training content not closely aligned with the actual situation; and a lack of diverse training methods.

Therefore, more investment in training is needed, along with increased training programs to encourage farmer participation and improve production efficiency.

2.2 Analyzing Financial Indicators In The Model

Table 1. Financial ratios of white radish farming households across seasons

Indicators	**Value**	**Crop 1**	**Crop 2**	**Crop 3**	**Crop 4**	**Crop 5**
Average Revenue/Total Cost	Average	2.1	2.7	3.4	2.5	2.6
	Minimum	1.0	1.4	1.5	0.5	1.4
	Maximum	3.7	5.2	7.2	7.0	4.9
	Standard Deviation	0.64	0.72	1.13	1.18	0.78
Profit/Revenue	Average	0.3	0.5	0.6	0.6	0.5
	Minimum	-0.4	0.1	0.2	0.2	0.1
	Maximum	0.6	0.7	0.8	0.8	0.7
	Standard Deviation	0.22	0.13	0.14	0.14	0.13
Indicators	Value	Crop 1	Crop 2	Crop 3	Crop 4	Crop 5
Profit/Total Cost	Average	0.8	1.7	2.1	2.1	1.4
	Minimum	-0.4	0.4	0.3	0.3	0.2
	Maximum	2.1	4.2	5.6	6.4	3.5
	Standard Deviation	0.60	0.72	1.1	1.16	0.74

	Revenue/Total Costs	Profit/Revenue	Profit/Revenue
Average	3.04	0.53	1.72
Minimum	1.42	0.17	0.24
Maximum	5.36	0.73	3.83
Standard Deviation	0.81	0.11	0.77

The empirical analysis of financial efficiency ratios, as summarized in the table, reveals significant fluctuations across the five cropping cycles. The Revenue-to-Total Cost (RTC) ratio for the first crop ranged from a minimum of 1.0 to a maximum of 3.7, with an overall mean of 2.1. This indicates that, on average, every 1,000 VND of total investment generated 2,100 VND in gross revenue.

The highest efficiency was observed in the third crop, where the RTC ratio peaked at 3.4. Given that the average RTC ratios across all five cycles consistently exceeded 1.0, the white radish cultivation model is considered generally profitable, particularly during the third cycle.

Regarding the Profit-to-Revenue (PR) ratio, or profit margin, the highest performance was recorded in the third and fourth crops at 0.6. This implies that for every 1,000 VND of revenue generated, farmers retained 600 VND as net profit, representing a 60% value retention rate of the total production value. Conversely, the first crop exhibited the lowest PR ratio at -0.4, indicating a net loss of 400 VND for every 1,000 VND of revenue, reflecting poor financial performance during this specific period.

The average Profit-to-Total Cost (PTC) ratio across the five cycles was 1.62, suggesting that a capital expenditure of 1,000 VND yields a net profit of 1,620 VND. However, the volatility of this model is evidenced by the first crop's minimum PTC value of -0.4, where farmers incurred a loss of 400 VND for every 1,000 VND of production costs invested. These results highlight that while the model is profitable on average, seasonal risks significantly impact the financial stability of white radish smallholders.

2.3 Model of Factors Affecting Profitability

The multiple regression model used to identify the factors affecting the profitability of white radish farmers is as follows:

$$Y = \beta 0 + \beta 1GT + \beta 2TUOI + \beta 3TĐHV + \beta 4DT + \beta 5KINHNGHIEM + \beta 6TAPHUAN + \beta 7SOVU + \beta 8LDGD + \beta 9LDT + e$$

In the white radish farming activities of households, several factors can potentially affect profitability, such as: gender (GT), age (TUOI), educational level (TĐHV), cultivated area (DT), production experience (KINHNGHIEM), training participation (TAPHUAN), number of white radish crops (SOVU), family labor (LDGD), and hired labor days (LDT).

The results of the analysis of factors affecting the profitability of white radish farming households are shown as follows:

Table 2. Results of estimating factors affecting profit

Variables	Coef.	T value	Sig	VIF
Constant	26470.231	7.502	0.000	
Gender (X1)	-2223.982	-2.976	0.004	1.140
Age (X2)	-58.338	-1.554	0.126	1.184
Education Level (X3)	39.686	0.276	0.783	1.187
Area (X4)	308.055	1.747	0.087	1.344
Experience (X5)	242.341	3.303	0.002	1.123
Training Participation (X6)	-1381.475	-1.041	0.303	1.251
Number of White Radish Crops (X7)	-3108.282	-7.679	0.000	1.128
Family Labor (X8)	450.856	1.218	0.229	1.391
Hired Labor Days (X9)	-2023.426	-3.023	0.004	1.136
Number of Observations	60			
Sig. F	0.000			
R^2	0.682			
Adjusted R^2	0.624			
Durbin-Waston	1.524			

According to the regression analysis results, the significance level of the model (Sig.F = 0.000) is less than 0.05, so the regression model is considered significant, meaning that at least one independent variable influences the dependent variable Y. The Durbin-Watson coefficient and the VIF coefficient of the model show that there is no autocorrelation or multicollinearity. The adjusted R2 coefficient is 0.624, meaning that 62.4% of the variation in household profits is explained by the factors identified in the model. In other words, approximately 62.4% of the variation in profit is influenced by age, education level, cultivated area, production experience, participation in training, number of radish crops, number of family laborers, and hired labor days. The remaining 37.6% is due to the influence of other factors.

Based on the analysis results in the table, out of the 9 variables included in the model, 5 variables are statistically significant (Sig. <10%), namely gender, area, experience, number of crops, and number of hired labor days. From the above results, the regression equation estimating the factors affecting the profit of white radish farming households is presented as follows:

$$Y = 26470.231 - 2223.982X1 + 308.055X4 + 242.341X5 - 3108.282X7 - 2023.426X9$$

From the regression equation, it can be seen that the independent variables included in the model are all significant (at the 5%, 10% significance levels)... This shows the impact of these independent variables on the model's profit as follows:

Gender: The results show that gender is inversely proportional to profit. If the household head is male, profit decreases by 2,223,982 VND/1,000m2 with other factors remaining constant. This result tends to differ from other studies, which generally show that male laborers in agricultural production are more efficient than female laborers because they can handle heavy work and are more daring in investing in production. It's possible that growing white radishes is relatively easy, activities such as sowing, harvesting, and cleaning radishes are more suitable for women, while land preparation can be outsourced. These reasons lead to lower profits for white radish growers with male heads compared to female heads.

Area: The area of land used for growing white radishes by the household is directly proportional to profit. - When the area of white radish cultivation by a household increases by 1,000 m2, with other factors remaining constant, the profit from white radish cultivation increases by 308,055 VND/1,000 m2/season.

Experience: The production experience of a household has a positive correlation with profit. This means that, with other factors remaining constant, an increase of one year in the household's experience in white radish cultivation will result in an increase of 242,341 VND/1,000 m2/season. This shows that the more experienced the household, the higher the profit. Experienced households have better seed selection and better methods of caring for and managing white radishes compared to less experienced households. Furthermore, during the cultivation process, experienced households can detect pests and diseases early, limiting their spread and preventing their formation and development. Number of crops: The number of crops of white radish is inversely proportional to profit.

Increasing the number of crops by one, with other factors in the model remaining constant, will reduce profit by 3,108,282 VND/1,000 m2. This shows that the more crops a farmer grows of white radish, the lower their profit will be. This could be due to the continuous and prolonged use of fertilizers and pesticides without allowing the soil to rest or improve its quality, leading to nutrient depletion and affecting both yield and radish quality. Therefore, it is necessary to adjust the number of crops and planting time appropriately to achieve better productivity and marketability.

Hired labor days: The number of hired labor days is inversely proportional to profit. Increasing the number of hired labor days by one, with other factors in the model remaining constant, will reduce profit by 2,023,426 VND/1,000 m2.

CONCLUSION

This research utilized primary data from 60 smallholders in Mekong Delta Vietnam, to evaluate the financial efficiency and determinants of profitability in white radish cultivation. The findings indicate a positive trend in land allocation toward white radish production over recent years. However, a significant knowledge gap persists; the majority of farmers possess limited formal education and lack access to specialized technical training, resulting in a production model heavily reliant on traditional experience rather than modern agro-technological advancements.

The research identifies multifaceted constraints that impede financial performance. Internal challenges include fragmented landholdings, seasonal labor shortages, and a profound lack of formal contractual agreements or integrated linkages between producers and agribusinesses. Externally, farmers are increasingly vulnerable to climate-induced weather volatility—which escalates pest pressure and reduces yields—and a price-cost squeeze characterized by unstable output prices and rising input costs. Furthermore, informational asymmetry remains high, as farmers predominantly depend on informal networks, such as traders or neighboring peers, for market intelligence. Econometric analysis via a multivariate regression model reveals that profitability is significantly influenced by gender, cultivated area, farming experience, cropping intensity, and hired labor requirements.

Specifically, farm size and years of experience exhibit a positive correlation with net returns, suggesting the presence of economies of scale and the critical role of tacit knowledge. Conversely, gender, excessive cropping cycles, and high reliance on hired labor were found to be inversely related to profit margins.

To optimize financial outcomes and enhance local livelihoods, it is recommended that farmers expand their production scale where feasible and recalibrate labor allocation and cropping schedules. Transitioning from experience-based to knowledge-driven agriculture is essential; this requires proactive engagement with technical training, agricultural extensions, and digital information platforms. Strategic solutions must focus on aligning production with climate resilience and market demand, improving the quality of vocational training, and formalizing supply chain linkages through robust contracts. Finally, embracing digital transformation and integrating e-commerce platforms will be pivotal in diversifying market outlets and ensuring the sustainable development of the white radish sector in study area.

Recommendations

Recommendations for Stakeholder Engagement and Policy Implementation: To ensure the effective execution of the aforementioned solutions, the following strategic recommendations are proposed for relevant authorities and organizations:

Local Government

Institutional Coordination: The local administration should strengthen public-private partnerships (PPPs) with agro-chemical firms and agribusinesses to facilitate technical training and resource management workshops for smallholders.

Communication Strategy: Collaboration with media agencies is essential to disseminate information regarding the collective economy. This includes educating farmers on the socioeconomic benefits of cooperative participation and international quality standards (e.g., VietGAP, GlobalGAP) to align production with global market demands.

Linkage Facilitation: Local authorities must create an enabling environment for processing and exporting enterprises to engage with farming households. By formalizing vertical linkages—covering input provision (technology, seeds, fertilizers) and output guarantees—the government can mitigate market volatility risks and ensure price stability through legally binding contracts.

Specialized Departments and Provincial Agencies

R&D and Technological Integration: The Department of Agriculture and Rural Development (DARD), in coordination with the Department of Science and Technology, should allocate R&D funding for climate-resilient white radish cultivation. Priority should be given to innovations that optimize input costs and enhance crop adaptability to environmental stressors.

Trade Promotion and Awareness: DARD should advise the Provincial People's Committee on organizing seminars to foster a "linkage mindset" among cooperatives and farmers. Strengthening trade promotion activities is critical to establishing stable, high-value distribution channels.

Digital Transformation: A multi-sectoral coalition—comprising the Department of Information and Communications, the Department of Industry and Trade, and logistics providers (Vietnam Post, Viettel Post)—should be formed to accelerate digital adoption. This involves onboarding farmers onto e-commerce platforms to diversify market outlets and improve brand visibility.

Agricultural Extension: DARD should mandate extension officers to provide on-site technical guidance, focusing on standardized "good agricultural practices" (GAP) to harmonize quality across smallholder plots.

The Scientific Community: Applied Research: Scientists are encouraged to deepen research into high-yield, pest-resistant varieties and bio-input technologies (bio-fertilizers and bio-pesticides). Effective technology transfer to local farming systems is vital for producing high-quality, market-compliant products while reducing environmental externalities.

Agribusinesses and Enterprises: upply Chain Sustainability: Technology firms and postal enterprises must maintain long-term strategic alliances with cooperatives.

By committing to forward-purchasing contracts and providing financial or technical subsidies, businesses can secure a stable supply of raw materials for processing while guaranteeing sustainable income for farmers.

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CHAPTER 3
REVOLUTIONIZING FOOD SAFETY THROUGH BLOCKCHAIN TECHNOLOGY

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INTRODUCTION

The food industry's success depends on consistently producing high quality, safe food considering the entire journey from farm to fork. Therefore, supply chain management must coordinate all the interconnected processes from raw material production to finished product delivery (Ellahi et al., 2023). The trade of commodities and information across international borders has increased dramatically as a result of the constantly changing global food supply chains and marketplace (Behnke et al., 2020). However, there is an imperative demand for improved credibility and information exchange because fraud, ineffective transactions and subpar performance inside FSCs have created questions about the authenticity and quality of items (Duan et al., 2020). Globalization, cultural norms, human behavior and regulations are just a few of the many variable that affect food supply chain networks. Effective information analysis and risk management in the industry are made extremely difficult by the intricacy of these aspects (Ellahi et al., 2023). To solve these issues and guarantee effective supply chain management, technology and knowledge must be developed immediately. There has been a lot of pressure on the global food supply chain, promote trustworthy information interchange and improve transparency (Kumar et al., 2020). Definitely, businesses all over the world have been changed significantly, specially in the sector of supply chain management, since traditional food supply chains become outdated in the current era due to a number of issues pertaining to food traceability, safety, fraud, poor monitoring, quality of food, and inadequate policies (Vistro et al., 2022). Moreover, companies are increasingly obligated to deliver extensive information on product-specific characteristics including accuracy, provenance, safety, authenticity, quality standards and traceability across the entire food supply chain, as a result of consumers' rising demand for the year-round availability of food products. Additionally, companies now have a big challenge to provide data about product specific attributes like safety, standards, provenance, accuracy, originality and traceability throughout the food supply chain, due to consumers growing demand for year round availability of the food items (Rejeb & Rajeb, 2020). Because of their reliance on paper based procedures and insufficient adoption of technology, food traceability systems opacity poses questions around proprietary and intellectual property.

When transmitting sensitive information within the food supply chain, this can jeopardize the trust and accuracy of the data. Successful product tracking and tracing requires consistent shared information, which is difficult for conventional monitoring systems such as bar codes to provide because of the issues with data accuracy, interoperability and fragmentation. Because blockchain may change supply chain structure and design and increase visibility and traceability, experts view it as a solution to FSC problems. Secure information sharing and storage are made possible by blockchain, a digital and decentralized ledger (Ellahi et al., 2023). Because of its traceability and resistance to manipulation, this transparent and unchangeable chain of blocks appeals to FSCs (Kumar et al., 2020). Because of its distinctive attributes, such as security, self- governance and anonymity, this contemporary breakthrough that combines several technologies is attracting interest from both academia and industry (Zhu & Kouhizadeh, 2019) . Blockchain technology, which was first presented by Satoshi Nakamoto in 2009, works as a decentralized ledger that permits network-wide consensus on data ownership (Ellahi et al., 2023). This networks does not require a centralized authority because nodes, coordinate independently or individual devices (Zhu & Kouhizadeh, 2019).

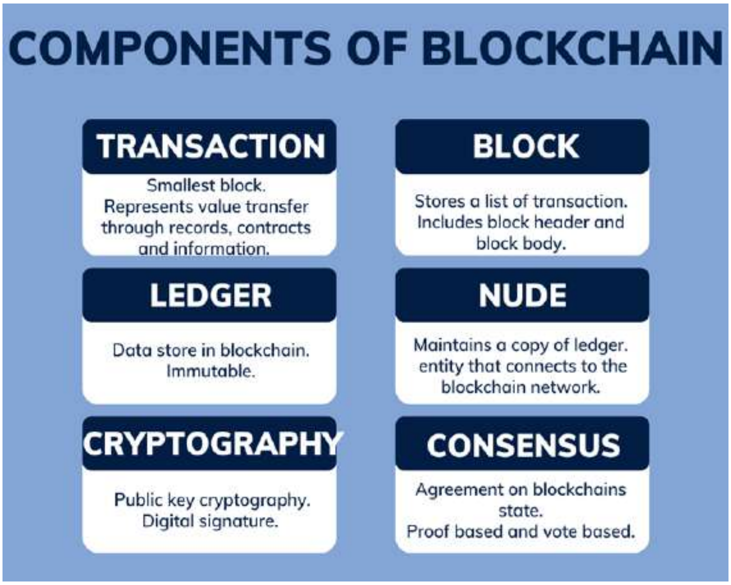

Figure 1. Components of blockchain (Idrees et al., 2021)

1. TRACEABILITY OF FOOD

Food traceability is defined by the Codex Alimentarius Commission and the International Organization for Standardization as the capacity to monitor or trace the movement of a product (such as food or feed) through the food chain process, including production, processing, and distribution (Qian et al., 2020). The American Production and Inventory Control Society defines food traceability in terms of ensuring food safety to a further degree 18. Relying on the precise information required along the supply chain, several drives or certain factors frequently determine the need of food traceability. There are five groups 1) quality and safety, 2) sustainability, 3) certification and laws, 4) efficiency and value, 5) sustainability (Islam et al., 2021).

2. TRADITIONAL TRACEABILITY METHODS

Traditional Traceability Methods and Purpose (Hassoun et al., 2024)

Table 1. Traditional Traceability Methods and Purpose

Method	Purpose	Detection	Example
Documentbased System	Product tracking and record verification	Stores food information (origin,expiry,composition, processing conditions allergens) via readable codes	Labels, QR codes, official documents used across farm to forksupplychain
Chromatography(GC , HPLC, LC)	Verify origin & detect adulteration	Separateschemical comonents to create product fingerprints	GC-FID used to classifyavocado by cultivar and origin
Mass Spectrometry	Authentication, chemical profiling, freshness detection,	Identifies fraud detection and molecular compounds for classification	Ambient MS distinguished fresh vs frozen fish and used for tracing origin of sugar
Trace Element Profiling	Identify origin	Identify elemental composition unique to water,soil,and environment	ICP-MS classified origin of cuttlefish

Method	Purpose	Detection	Example
Stable Isotope Analysis ($\delta^{13}C$, $\delta^{15}N$)	Identify farming practices and production system	Isotope ratios reveal region,diet, and farming system	Differentiated organicvsconventional; wild vs farmed fish
Fatty Acid Profiling	Authenticity and Product origin	Lipid biomarkers used to trace geography	Used to trace goat milk from different regions
DNA-based Techniques (barcoding, PCR)	Adulteration detection and Species identification	Detects species composition in raw and processed foods	33% fish products found mislabeled
NGS	Detect species in complex mixtures	High-resolution DNA identification in complex foods	Used to identify meat species in mixed meat products
Immunological Technique (ELISA)	Detect allergens and contaminants	Identifies allergens, pesticides, toxins, heavy metals	Used for food hazards analysis
Protein-based Analysis (Electrophoresis)	Detect product composition & processing history	Identify proteins to reveal biomarkers	Parvalbumin protein used to differentiate fresh vs frozen fish

3. TYPES OF BLOCKCHAIN

Blockchain technology primarily comes in two varieties; private blockchain and public blockchain. However, depending on additional factors and study, Blockchain technology can also be referred to consortium blockchain technology. Blockchain technology is divided into the following three categories based on its broad nature (Gamage et al., 2020), (Sakhipov & Baygozhanova, 2020).

- Private Blockchain
- Public Blockchain
- Consortium Blockchain

Private Blockchains

This type is restricted and closed off, but have certain features of access. With the help of system administrator, this blockchain permits the transaction (Paul et al., 2021). The platforms with the functionalities are developed by private blockchain solutions of the following: High efficiency, Better scalability, Complete privacy, Faster transactions and Faster and speediness. This type of blockchain only works on closed systems and networks, which are particularly helpful in businesses and organizations where only a limited number of people may take a part. This kind of blockchain has suitable authorization, permission, accessibility and security. Experts claim that private blockchains are utilized for voting, digital identity discovery, supply chain management, ownership and other purposes. Multichain, Corda, Hyperledger projects, etc are some popular private blockchains.

Public Blockchain

Public blockchain is one of the popular type of blockchain, which is both open and decentralized. Moreover, anyone involved in transactions can essentially access computer system using this type of blockchain technology. In addition to receiving the transaction rewards, two types of Proof-to-stake and Proof-of-work models are employed. Additionally, the Public Blockchain is a distributed ledger system that is non restrictive and there is no need of any type of permission. Anyone with access can be authorized to obtain data of the Blockchain. Additionally, this kind of blockchain authorizes the verification of both past and present records. This is also used for cryptocurrency missing and trading (Lin et al., 2020 ; Williams, P. 2019). The most popular blockchains in this category are Litecoin and Bitcoin. When stringent security directions and procedures are followed, it became safe. But, it could be unsafe if the security rules and regulations are not followed. Ethereum, Bitcoin, and Litecoin are some examples of public blockchain.

Consortium Blockchain

It is a different kind of semi-decentralized blockchain that may be used to manage the blockchain network.This kind of blockchain can function even from a single company.

In this case, blockchain can share data or engage in mining and are utilized in sectors including government and banks, and among others. Examples of this kind of cooperation include the Energy Web Foundation, R3, and others (Paul et al., 2021).

In summary, each blockchain has its own benefits and advantages, both private and public blockchains are considered as significant in terms of their operations.

4. APPLICATIONS OF BLOCKCHAIN IN FOOD TRACEABILITY

Single point of failure and data manipulations are issues linked to the increasingly centralized traceability systems currently in use with centralized data centers (Liu et al., 2022). A data structure called blockchian was created to facilitate the use of distributed digital ledgers, which store data securely in chained blocks (Zarpelão et al 2021). Despite its widespread use in the financial sector, BCT is seen by a number of other industry sectors as a significant catalyst for paradigm change, and it has received more attention recently (Bosona et al., 2023). International standards such as ISO 22739:2020-Blockchain and distributed ledger technologies Vocabulary and ISO 23257:2022-Blockchain and distributes ledger technologies-References architecture (ISO, 2022), are being established to make the use of BCT easier. As a result, it can create a reliable traceability information of flow between supply chain players (Varavallo et al., 2022). Nevertheless, little is known about how to create a conceptual design, framework, and apply BCT for product tracking, particularly in complex AFSCs with mixed information from multiple sources, which makes the traceability system a multidisciplinary procedure (Zhang et al., 2022).

The logistics of the food supply chain are increasingly dependant on real-time monitoring technologies (Bosona et al., 2023). Because BCT makes it possible to develop a decentralized, transparent, automated, immutable, and dependable system for decision making and real time monitoring, its use in AFSCs is crucial (Leduc et al., 2021).

IoT technologies like radio frequency determination have been used extensively in the implementation of digital food traceability systems, but BCT based traceability systems are starting to show promise as a viable alternative (Gayialis et al., 2022). The difficulty of creating a common traceability structure that allows traceability systems (for different food product value chains)to function while maintaining flexibility, adaptability and scalability of the solutions means that, despite the development and implementation of specific traceability systems in AFSCs, there is no other traceability system that can meet all the needs of the different food supply chains (Bosona et al., 2023). Thus, in the agri-food industry, the creation of an effective and efficient traceability systems is crucial. In order to facilitate this endeavor, the agri-food industry is conducting more research on BCT-based traceability systems, and new businesses have recently surfaced (Mirabelli et al., 2020). Reviews of BCT's use in agriculture, however are scarce (Demestichas et al., 2020; Rejeb et al., 2020) carried out a systematic review and examined the possible advantages and difficulties of BCT in the food business Yadav and Singh (Bosona et al., 2023) examined the use of BCT in the agricultural field; Major Industry 4.0 technologies and their applications in AFSCs were reviewed by Yadav et al. (Yadav et al., 2022), the applications of BCT in the agri-food sector by Antonucci et al. (Bosona et al., 2023), the importance of BCT and lot in the fight against product counterfeiting by Gayialis et al. (Gayialis et al., 2022), and the use of BCT for tracking in the agri-food sector by Demestichas et al. (Demestichas et al., 2020). More synthesis work is needed to encourage the use of BCT, which has a good potency to address issues in complicated AFSCs. The aforementioned restricted evaluations give a general overview of uses of BCT in the agriculture industry. There are currently no review studies that concentrate on the traceability of agricultural products using BCT. By examining studies that concentrate on traceability systems with incorporating BCT, the current study fills this gap. A larger body of knowledge is needed because the use of BCT based traceability is quiet in its early stages and no reliable and reasonably priced commercial solution has been created to yet (Zhai et al., 2022). For example. Nothing is known about the supply chain architecture and data structure requirements required for the successful implementation of BCT in AFSCs (Tsolakis et al., 2020).

Furthermore, nothing is known about the possible effects of using BCT based traceability systems in AFSCs (Compagnucci et al., 2022). In order to facilitate the further improvement and implementation of efficient BCT based traceability systems in the food sector, it is crucial to synthesize the existing research findings and present novel ideas (Demestichas et al., 2020).

Guaranteed Standards for Food Quality and Safety

Blockchain offers a revolutionary way to enhance food quality and safety in supply systems. Blockchain solves the issues of traceability gaps by ensuring end to end traceability, enabling stakeholders to trace food goods throughout their supply chain. Because blockchain's decentralized ledger offers an unchangeable record of ingredients validity, this reduces the risks related to adulteration. Blockchain's transparent and real-time data access makes it possible to quickly and accurately detected impacted food products during a food recall, minimizing health risks and financial losses. Moreover, blockchain improves efficiency of supply chain by reducing food waste. For example, Walmart successfully utilized blockchain to trace the origin of mangoes, cutting time from days to seconds. These developments demonstrate how blockchain technology may transform food quality and by fostering transparency, efficiency and trust across all over the supply chain (González-Puetate et al., 2022). The following are some benefits of blockchain technology in food sector to enhance the quality and safety of food products:

Enhancement of Traceability

Blockchain records' transparency and immutability prevent traceability loss, improving accountability and lowering the risk of fraud or contamination of food (Singh et al., 2023). Every food product has an uninterrupted chain of custody, thanks to the transparent and decentralized ledger. Every transaction is documented and time-stamped, starting at the farm and continuing through all supply chain tochpoints. This increased traceability facilities targeted recalls, reduces potential health concerns and aids in the prompt identifications and isolation of any contaminated or compromised products (Kampan et al., 2022).

Food Adulteration Prevention

The risk of food adulteration is greatly reduced by the temper-resistant nature of blockchain. Each product's history is secure and verifiable because to the blockchain's immutable records, which guarantee that details on ingredients, processing and quality certifications are preserved. This encourages the authenticity of food products and discourages fraudulent activity. Blockchain smart contracts have the ability to send out alerts in the event that the product's composition is tampered with or without altered the authorization. A decentralized ledger offers a safe and unchangeable record of every ingredient and its source, confirming the legitimacy of food items (Leung et al., 2021).

Reducing Food Waste

Perishable commodities can be distributed on time and overstocking can be avoided using real-time supply chain visibility. Business may better match supply with demand and reduce overstock situations, which frequently result in food waste,by cutting down on delays and inefficiencies in the distribution process. As a result, the food supply chain becomes more economically viable and sustainable. Blockchain enables targeted and quick recalls in the event of contamination or safety issues by providing rapid access to a a food product's whole history (Dey et al., 2022).

Figure 2. Role of Blckchain in food sector (Kampan et al., 2022), (Leung et al., 2021), (Leow, 2023), (Dey et al., 2022)

Blockchain Technology Driven Food Traceability

Food traceability is the process of tracing food products from animal raising to product shipment in stores in FSC. It contains information about animal, nutrition, health, breeding, farm management and production, food preservation and processing, packing , logistics and at the end, the consumer's plate (Patel et al., 2023). These days, buyers and stakeholders increasingly ask on evidence of food integrity and transparency. Real-time data tracking can speed up the supply chain and reduce food fraud at every stage of the product's life cycle. However, supervisors or supply chain management intermediaries may violate data in existing online and centralized observation or offline and paper based traceability systems. The traceability system is made irreversible, concrete, and impervious to any kind of dispute by BCT's unchangeable, consensus mechanism-driven online data recording system in the supply chain at every point of food production (Creydt & Fischer, 2019). A simple illustration of BCT-driven food traceability is a three layer flow, where the physical flow layer represents the actual food supply chain, where food items travel from producer to buyer. The second flow layer is for a digital record system where different kinds of sensors, QR codes, RFID and other digital technologies are used concurrently with data recording of the physical flow layer. The data captured in the second flow layer is validated by all participating bodies using a consensus method in the third flow layer, which is a digital blockchain infrastructure network. This creates a virtual data block at each point of the supply chain. This flow layer creates a sequence of digital data blocks and follows the physical flow layers as well (Kamilaris et al., 2019). It is an immutable and record-keeping platform because if someone attempts to hack or alter recorded data, the hash value of that specific block changes, preventing the altered value from entering that specific blockchain. The food product travels through several stages of manufacture on its route to the customer's plate, and at each stage, some data is entered into the blockchain, as explained below.

Stockmen

They offer details on how livestock are raised on farms, including information about the feeding, breeding, health, management and production methods used, as well as the tag number and ownership information of every animal,whether or not it is bought straight from the market. It is also possible to document the environmental and hygienic aspects of farm and animal care procedures (Patel et al., 2023).

Manufacturing Parties

Details about plant operations, livestock handling, the sanitary and hygienic state of a plant, regulations and standards upheld at the plant, availability of equipment, disinfection and utilization procedures followed at the plant, information about processing techniques, labeling specifics of each product batch, use of packaging technologies, etc. A block also contains information about the financial transactions that take place between a manufacture and logistic suppliers as well as between a producer and stock-men (Patel et al., 2023).

Logistic Suppliers

Information about the mode of shipping specifics, duration of transit and real-time data on temperature, transportation, humidity, and other product environmental conditions during transit. Additionally, the financial transactions between approved dealers and logistics suppliers must to be documented (Patel et al., 2023).

Dealers

Up-to-date information on the product's storage conditions, including time, humidity and temperature, until it is supplied to retailers. Is is also possible to record transportation data. Additionally, the financial exchange between retailers and dealers is documented (Patel et al., 2023).

Retailrs

The Blockchain records information about each product's current stock, expiration date and time, storage specifications, etc (Patel et al., 2023).

Buyer

Using an internet connection, the buyer scans the QR code on the product to obtain all the product's details, from farm to purchase, giving them a notion of the product's safety, quality, and dependability (Patel et al., 2023).

Figure 3. Value chain of milk from farm to fork (Patel et al., 2023)

5. CHALLENGES AND BARRIERS

The results of our study on BT's use in the food sector to access a variety of difficulties are presented in this section. The following are the unresolved problems and difficulties in integrating blockchain technology in the food industries, despite the fact that BT offers numerous advantages to the sector, including dependability and immutability.

Privacy

The food supply chain necessities privacy violations due to to the widespread usages of IoT devices sensing systems, which constantly collect data from their surroundings.

For instance, every node in the blockchain based supply chain system has a copy of the distributed record, which means that all participating nodes receive sensitive or private information (Gupta et al., 2020), (Kumari et al., 2020).

Scalability

In the food sector, a system's scalability is crucial. The BT is suitable for the transactions if there are fewer nodes, and the necessary speed can be enforced. However, it may be better to have a sufficient number of connected nodes and phases. Bitcoin and Ethereum are examples of blockchain systems that can process 12 transactions per second. To speed up transaction execution and transactions per second. To speed up transactions execution and enhance consensus methods, numerous new blockchain systems are being created (Hafid et al., 2020), (Bao et al., 2020).

Security

There are advantages and disadvantages to blockchain's decentralized structure. Blockchain is resilient to a variety of security threats, due to its nature, it is susceptible to a cyberattack known as a 51 percent attack (typically on bitcoins). Because of this, a prospector node controls node than half of the blockchain's hash rate and processing power. In food processing, this situation arises if a significant portion of the framework is compromised. Consequently, a strong reliable solution is required to increase the security of the entire food processing network based on blockchain (Singh et al., 2021). Smart contracts are a type of programming code that can be vulnerable to different security attacks due to the lack of appropriate programming modes. Testing smart contracts methods can be a way forward (Gupta et al., 2021), (Kushwaha et al., 2022).

Lack Of Rules and Standardization

Several organizations, including the TU and IEEE, are working to develop latest blockchain invention measures that facilitate blockchain integration with other technologies. To make blockchain implementations future proof, IEEE has undertaken a number of projects in blockchain benchmark; however, this calls for appropriate rules, regulations, ordinances, processes and laws.

Therefore, sophisticated blockchain implementations will continue to work with contemporary ones. In order to develop suitable specialized principles, guidelines and methods for the successful use of blockchain in the food business, some study should be done immediately (Niya et al., 2020; König et al., 2020).

Data Storage Capacity

One major problem that still needs to be investigated with blockchain technology is storage capacity. Nevertheless, the food processing system produces gigabytes of data in actual-time, which are difficult to handle (Xu et al., 2019). As a result implementing a food processing system that is compatible with blockchain technology is difficult. This might be a drawback of the decentralized, safe approach that is being suggested.

Data Storage Cost

Blockchain raises data storage costs while enhancing data security in the food production sector. In the Etherem blockchain, save each words (32 bytes, or 256 bits) takes 20 K Gas. The current price of gas is about 6gwei, and the Ethereum cryptocurrency (Ether) is worth USD 131. Therefore, ≈USD 57 is the ultimate value to save 1 MB in Ethereum.

Legal Challenges

A few issues to consider from a legal standpoint, the question is that whether blockchain technology is currently ready to carry out the duties of notaries, real estate agents, lawyers, land registries, and so on, guarantee a secure real estate transaction, given the potential uses of blockchain technology in the estate industry. To be regarded as trustworthy, secure and lawful as the existing real estate conveyancing systems in Europe, this technology must overcome a few obstacles. On the other hand, blockchain protocols have some general issues that apply to all industries, not only real estate. One issue with bitcoin, cryptocurrency and Ethereum, are the scalability of the network and the expenses related to smart contracts. The interested parties need Gas (transaction value) to complete an Ethereum smart contract, and even if the transaction is not completed, the parties must pay the required fee.

This is also related to the system' s scalability: when more transaction occur, miners receive greater reward to ensure that the transaction is completed. Moreover, creating a blockchain based database that records all EU real estate activities (such as leases, purchases, and other transactions) could make the verification process lengthy, increasing the need for additional miners and therefore raising transaction fees. Numerous researchers and developers actively seeking solutions to this issue for example, the fee-less IOTA cryptocurrency designed for the Internet of Things, which uses the Tangle system where miners are absent (Ahmad et al., 2024). Yet, for a real estate conveyancing framework, it would be preferable to control these costs such as through a permissioned blockchain where a central authority regulates fees, or a proof-of-authority model in which the administration validates transactions—so that individuals are not discouraged from registering their rights. Nonetheless, applying blockchain technology to a real estate conveyancing system introduces distinct difficulties, including managing the identification of parties and confirming that the contract recorded on the ledger is valid (Garcia-Teruel, R. M. 2020).

6. ARTIFICIAL INTELLIGENCE AND BLOCKCHAIN TECHNOLOGY INTEGRATION

One of the most well known inventions of our time, blockchain has drawn a lot of interest as a flexible technology that can be used in a variety of industries. The development of AI has been greatly aided by the exponential expansion and collection of data from sensor system, IoT devices,web applications and social media. Using a variety of machine learning techniques, this data can be utilized. Nevertheless, most AI techniques rely on a centralized model for training, in which a group of computers use training and validation datasets to run certain models. To make wise decisions, industry titans like Google, Facebook, Amazon and Apple manage massive amounts of data. One significant issue with centralized AI is the data's susceptibility to manipulation and hacking due to its centralized management and storage. Additionally, there is no guarantee regarding the data's authenticity and provenance from its sources. These issues may result in extremely hazardous, unsafe, and incorrect AI decision outputs (Kuznetsov et al., 2024).

Figure 4. Challenges and barriers to blockchain adoption (Ahmad et al., 2024)

The idea of decentralized AI, which combines AI with blockchain technology, has recently developed in response to these worries. Processing, decision making and analytically, digitally and trusted shared data that is transacted are made by decentralized AI. This method eliminates the need for reliable mediators or third parties by operating in a distributed and decentralized manner. Blockchain has become a reliable platform for safely storing the massive volumes of data that AI depends on. The capacity to design the blockchain to regulate transactions among participants participated in decision making or data generation and access is made possible by the functionality of blockchain smart contracts. The following succinctly describes the advantages of decentralized (Blockchain) AI (Kuznetsov et al., 2024):

- Improved data security

- Increased confidence in robotic decision-making
- Making decisions collectively
- Decentralized intelligence
- High efficiency

7. FUTURE DIRECTIONS

A number of different paths are being investigated in order to overcome the obstacles and fully utilize blockchain technology. Research and development into solutions aimed at boosting transaction throughput and decreasing network latency are being used to address the scalability issue. The basic main of strategies like side chains, state channels, sharding, and value chain scaling, is to enhance scalability while maintaining the traffic jams, fundamental ideas of security and decentralization (Makina et al., 2024). Another area of emphasis is interoperability, with the creation of frameworks like the Blockchain Interoperability Alliance and the Interledger Protocol that enable asset transfer and cross chain communication. By dismantling the barriers that separate various blockchain networks, these initiatives want to create a more interconnected and adaptable environment. To solve issues with data privacy and confidentially, privacy preserving solutions are being developed (Wang et al., 2023). Users have more control over their financial actions thanks to this permission-able paradigm, which also control over their financial industry. A novel approach to enabling decentralized governance and decision making is through Decentralized Autonomous Organizations. DAO decentralized collaboration on fraud management and governance procedure made possible by platforms, which facilities more inclusive and open decision making. Energy, entertainment and gaming are just a few of the industries where blockchain technology is being used. Consortium and cross-industry partnerships are investigating creative use cases that take advantage of blockchain's special qualities to solve certain problems (Sahoo et al., 2023). These initiatives are boarding the effect of blockchain technology. Compliance and regulations continue to be major issues.

To create precise regulatory frameworks and compliance requirements, legislators, industry stakeholders and regulators must work together. In order to promote innovations while guaranteeing consumer safety and investor trust, pilot projects, regulatory sandboxes, and instructions from authorities are essential. Incorporation of new technology, like IoT and AI presents a viable way to increase blockchain's capabilities. Predictive analytic, automated making and fraud detection, are made possible by convergence with AI, while safe, decentralized data interchange and management are made possible by IoT integration (Ahmad et al., 2023). These potential paths show how blockchain technology is always developing and has enormous potential to transform industries all around the world. Realizing the full revolutionary impact of blockchain on the digital economy with require on the digital economy will require ongoing study, cooperation and development.

CONCLUSION

Blockchain technology transforms food supply chain management by providing a secure, decentralized digital ledger that tracks every stage from farm to fork, ensuring transparency, traceability, data integrity. It addresses traditional challenges like fraud, inefficiencies, and outdated paper based systems by enabling real time product tracking and immutable data records accessible to all supply chain stakeholders. This significantly improves recall efficiency and reduces food safety risks. Blockchain come in private, public, and consortium varieties, with distinct privacy, scalability, and consensus mechanisms suited for different use cases. The integration of blockchain with IoT and digital sensors enhances supply chain visibility, enabling accurate monitoring of production, processing, storage and transportation conditions.

However, challenges persist around privacy, scalability, security (51% attacks), legal regulations data storage costs, and throughput. Advances in blockchain protocol design, regulatory frameworks, interoperability, and energy efficient consensus are essential for broader adoption. Further, merging blockchain with intelligence enables decentralized, trustworthy, data analysis and decision making, improving fraud detection and operational efficiency.

Industry applications such as IBM Food Trust, Walmart, Provenance, and TE-Food, demonstrate blockchain's ability to shorten traceability timeliness dramatically and enhance supply chain sustainability. Overall, blockchain offers a revolutionary approach to securing food supply chains that ultimately raises consumer confidence, improves food safety and quality, reduces waste, and streamlines compliance across the global food industry ecosystem. Continued innovations and collaboration among stakeholders are critical to fully realize blockchain's trans-formative potential in food systems.

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