

ARTIFICIAL INTELLIGENCE AND DIGITAL TRANSFORMATION OF AGRICULTURE: A PATHWAY TO SUSTAINABLE DEVELOPMENT

Sadig Sarvan oglu ISAYEV

Baku Business University, Azerbaijan

Annotation. The study examines the prospects of digital transformation and the application of Artificial Intelligence (AI) in modern agriculture as a response to global challenges of food security, climate change, and resource scarcity. The main purpose is to analyze how AI-based technologies—such as machine learning, IoT, and predictive analytics—enhance agricultural efficiency, sustainability, and decision-making. The research employs an analytical and comparative approach based on recent literature and global case studies from the United States, the European Union, China, and India. Findings indicate that AI enables precision irrigation, optimized resource allocation, and improved yield prediction, thereby reducing costs and environmental impact. However, barriers such as low digital literacy, limited infrastructure, and insufficient investment remain pronounced in developing economies. The case of Azerbaijan illustrates both emerging potential and persistent challenges in implementing smart agriculture initiatives. The study concludes that successful AI integration requires coordinated policy frameworks, digital capacity-building, and multi-sector collaboration to achieve sustainable agricultural transformation.

Keywords: Artificial Intelligence (AI); Digital Transformation; Agriculture 4.0; Smart Farming; Sustainable Development; Azerbaijan

INTRODUCTION

Agriculture remains a cornerstone of human development, ensuring food security, employment, and ecological stability. Yet in the twenty-first century, it faces profound challenges stemming from climate change, soil degradation, resource scarcity, and the need to feed a growing global population. According to the FAO (2023), agricultural production must increase by nearly 50 percent by 2050 to meet future demand, even as available land and freshwater decline. These pressures make traditional farming systems insufficient and call for a structural transformation toward technology-intensive, data-driven agriculture. Over the past decade, scholars have increasingly highlighted Artificial Intelligence (AI) and digital technologies as enablers of this transformation. Research by Zambon et al. (2019) and Kamilaris & Prenafeta-Boldú (2017) demonstrates that integrating Big Data analytics, Internet of Things (IoT), and machine learning into agriculture significantly enhances productivity and resource efficiency. At the same time, Bronson (2019) and Kawasaki & Kameoka (2020) stress that the digitalization of agriculture must balance technological progress with environmental sustainability and social inclusion—core principles of the Sustainable Development Goals (SDGs).

Despite growing attention to AI in agriculture, substantial research gaps remain. Most studies focus on developed countries with mature digital ecosystems, while emerging economies—such as Azerbaijan—lack comprehensive analysis of how AI can be systematically integrated into agricultural policy and practice. The scientific relevance of this study therefore lies in expanding the theoretical and empirical understanding of AI's role in transitioning traditional farming toward sustainable, innovation-driven systems. The practical relevance stems from providing a policy-oriented framework for applying AI tools in irrigation management, yield forecasting, and smart-village development, which are critical to improving efficiency and rural welfare.

Accordingly, this research aims to analyze how AI technologies are currently applied in agriculture, their socio-economic and environmental effects, and the prospects for wider implementation. The central research questions are:

- What are the main directions of AI application in agriculture?
- What are the expected economic, environmental, and social outcomes?
- What barriers and opportunities exist for developing countries, particularly Azerbaijan?

The study employs an analytical and comparative approach based on literature from 2020–2024 and global case studies from the USA, EU, China, and India. By bridging global insights with national experience, it contributes both to the scientific discourse on Agriculture 4.0 and to the practical design of inclusive, sustainable agricultural policies.

THEORETICAL AND CONCEPTUAL FRAMEWORK FOR AGRICULTURE AND DIGITAL TRANSFORMATION

Agriculture, historically the backbone of human civilization, remains indispensable for ensuring food security, employment, and sustainable economic growth. In the 21st century, its importance has expanded beyond mere food production — it now encompasses ecological stability, social equity, and economic resilience. As noted by Conway (2012) in *One Billion Hungry: Can We Feed the World?*, agriculture must simultaneously increase yields and preserve natural resources if humanity is to meet the nutritional needs of a projected 9.7 billion people by 2050 (Conway, 2012, p.

18). However, traditional farming methods—largely dependent on natural conditions and manual labor—are increasingly inadequate against the backdrop of climate change, soil degradation, and demographic pressures. Hence, the transformation of agriculture into a digitally driven, intelligent, and sustainable system is not optional but imperative.

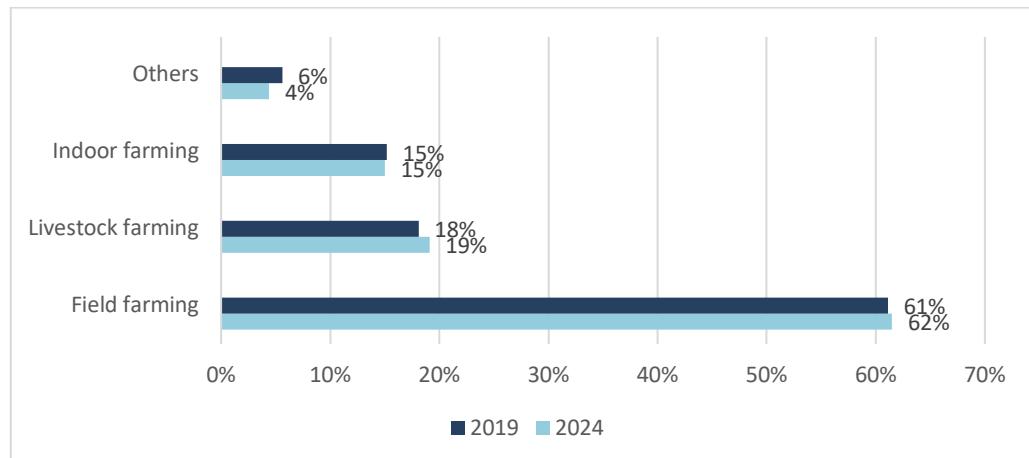
The Sustainable Development Theory posits that true development must balance economic efficiency, environmental preservation, and social inclusion. In agriculture, this triad translates into producing “more with less”—increasing productivity while conserving soil, water, and biodiversity. According to Sachs (2015) in *The Age of Sustainable Development*, the agricultural sector is “the decisive battlefield for sustainability” as it both depends on and affects ecosystems (Sachs, 2015, p. 209). Digital transformation supports this balance by reducing inefficiencies, optimizing input usage, and enhancing decision-making accuracy. AI-driven platforms can help reduce food loss, minimize chemical overuse, and optimize irrigation patterns, thereby aligning productivity with environmental responsibility. In contrast, critics such as Altieri and Nicholls (2020) argue that overreliance on technology risks marginalizing small farmers and may exacerbate inequality (Altieri & Nicholls, *Agroecology and Sustainable Food Systems*, 2020, p. 27). Nevertheless, such challenges underscore the need for inclusive digitalization policies rather than negating the benefits of AI.

The integration of digital technologies—notably the Internet of Things (IoT), Big Data, Artificial Intelligence (AI), and blockchain—forms the core of this transformation. The Food and Agriculture Organization (FAO) describes these technologies as “digital accelerators” capable of enhancing efficiency, productivity, and sustainability across all stages of the agricultural value chain (FAO, *Digital Agriculture Report*, 2022, p. 12). IoT devices collect real-time data on soil moisture, temperature, and nutrient content; Big Data analytics process and interpret these vast datasets; AI algorithms transform raw data into predictive insights; and blockchain ensures transparency and traceability in supply chains. For instance, Kamilaris et al. (2017) highlight that IoT-based precision agriculture reduces water use by up to 30% and fertilizer use by 25% without yield loss (Kamilaris et al., *Computers and Electronics in Agriculture*, 2017, p. 141). This evidence demonstrates how digital tools directly contribute to sustainability goals by improving efficiency while conserving natural resources.

Artificial Intelligence serves as the analytical engine of digital agriculture. Machine learning, deep learning, and predictive analytics enable farmers and policymakers to make evidence-based decisions. AI systems are increasingly used for “crop yield prediction, soil quality assessment, pest identification, and resource optimization,” marking a paradigm shift from reactive to proactive management. For example, convolutional neural networks (CNNs) can detect early-stage crop diseases through image analysis, while predictive models based on historical climate and soil data help optimize planting schedules. Zhang and Kovacs (2019) show that deep learning integrated with remote sensing improves yield estimation accuracy by 15–20% compared to traditional statistical models (Zhang & Kovacs, *Remote Sensing of Environment*, 2019, p. 95). Critics such as Bronson (2019) caution that such AI systems can create “data asymmetries” favoring large agribusinesses over smallholders (Bronson, *The Journal of Peasant Studies*, 2019, p. 8), yet this reinforces the need for open-data frameworks and digital literacy programs to ensure equitable access.

Parallel to AI, data-driven and precision farming represent practical embodiments of this technological transformation. These approaches rely on real-time monitoring systems—sensors, drones, and analytics—to apply the right amount of water, fertilizers, and pesticides at the right time and place. As Gebbers and Adamchuk (2010) explain, precision agriculture transforms traditional field management into “site-specific crop management,” reducing both costs and ecological footprints (Gebbers & Adamchuk, *Science*, 2010, p. 825). Unmanned aerial vehicles (UAVs) equipped with multispectral cameras can identify pest infestations or nutrient deficiencies before they become visible to the human eye. These practices embody the Sustainable Development Theory in action—where technological innovation directly supports ecological conservation and social welfare.

The following diagram shows AI in Agriculture market share by farming type:



Picture 1. Global Artificial Intelligence in Agriculture market share by farming type

Source: Market.us scoop

Picture 1 illustrates the global AI in agriculture market share by farming type for 2019 and 2024. According to Market.us Scoop (2024), field farming continues to dominate the market, maintaining a stable share of around 61%, which reflects its critical importance in large-scale agricultural operations. Livestock farming shows moderate growth, increasing from 18.1% in 2019 to 19.1% in 2024, largely due to the adoption of AI-based health monitoring and feed optimization systems. Meanwhile, indoor farming exhibits a slight decline from 15.2% to 15%, likely resulting from high operational costs and limited scalability. The “others” category decreases from 5.6% to 4.4%, suggesting consolidation of AI applications in the more dominant sectors. Overall, these Pictures indicate that while AI adoption is expanding across all farming types, the most significant advancements remain concentrated in traditional field and livestock farming activities.

Finally, Agriculture 4.0 encapsulates the convergence of these digital tools within the broader context of the Fourth Industrial Revolution. It represents a system in which physical and digital dimensions of agriculture are intertwined through cyber-physical systems, robotics, IoT, and AI. As Zambon et al. (2019) note, Agriculture 4.0 allows “real-time monitoring, autonomous decision-making, and predictive maintenance,” creating self-regulating ecosystems (Zambon et al., Computers and Electronics in Agriculture, 2019, p. 357). The outcome is a paradigm shift from mechanization to intelligent automation. However, the transition requires not only technological readiness but also supportive institutional frameworks, data governance, and farmer training to ensure inclusiveness and sustainability.

The global agricultural sector is undergoing a profound transformation as nations integrate artificial intelligence into farming systems, driven by the need to enhance productivity, sustainability, and resilience. The transition toward “smart agriculture” is not merely technological—it reflects a global response to food security challenges, climate variability, and the imperative of efficient resource management. According to the Food and Agriculture Organization (FAO, The State of Food and Agriculture, 2023, p. 47), the adoption of AI technologies in agriculture is projected to grow annually by over 20% through 2030, underscoring its strategic role in shaping sustainable food systems.

In developed economies such as the United States, the Netherlands, and Japan, AI-driven innovations have redefined agricultural practices through automation and data analytics. In the U.S., companies like John Deere have introduced autonomous tractors and machine-learning-based precision equipment capable of optimizing planting and harvesting decisions. Similarly, the Netherlands, known for its highly efficient agricultural model, employs AI-powered smart greenhouses that use predictive climate models and computer vision to regulate temperature, irrigation, and nutrient flow, achieving yields up to 40% higher than conventional systems. In Japan, robotics and AI integration have become central to addressing labor shortages in aging rural populations. Automated rice transplanters, crop-monitoring drones, and AI weather models are part of the “Society 5.0” vision, linking digital ecosystems to rural productivity (Kawasaki & Kameoka, Technological Forecasting and Social Change, 2020, p. 221).

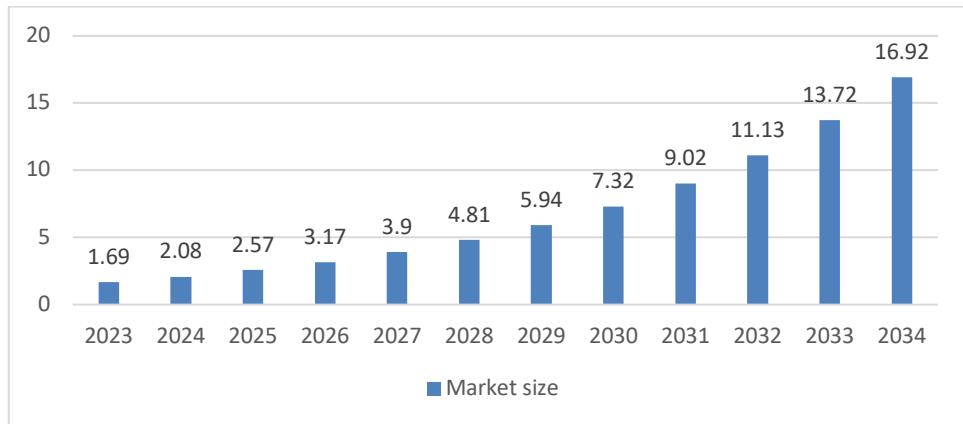
Meanwhile, developing economies are increasingly leveraging digital tools to overcome structural barriers. India has introduced mobile-based AI advisory platforms such as Digital Green and e-Choupal, which disseminate real-time agronomic advice and market information to millions of smallholder farmers. Empirical assessments indicate that such digital extension services have improved income stability and crop yield by 15–20% (World Bank Policy Research Working Paper, 2022, p. 37). Besides, India and the US launched the US-India AI Initiative (USIAI) through Indo-U.S Science and Technology Forum (IUSSTF), a jointly funded autonomous organization. This initiative enables India to harness American AI technology to enhance food grain production in agriculture.

China, a global leader in agricultural digitalization, has invested in AI-based pest detection systems and blockchain-enabled traceability platforms, reducing post-harvest losses and improving supply chain transparency. In Brazil, AI-supported satellite imagery and predictive analytics have been widely applied in monitoring deforestation and optimizing soybean cultivation in the Amazon Basin (da Silva et al., Sustainability, 2021, p. 6125).

A comparative analysis of these cases reveals that successful digital transformation in agriculture depends on more than technology itself—it requires robust policy support, institutional coordination, and human capacity development. Countries that have established innovation ecosystems—linking research institutions, agri-tech startups, and public agencies—achieve faster diffusion of AI applications. For instance, the U.S. Department of Agriculture’s AI Institutes network and the European Union’s “Farm to Fork” digital strategy illustrate how regulatory frameworks can encourage innovation while maintaining ethical standards and data privacy (OECD, Digital Agriculture Policies Review, 2023, p. 76). Conversely, in many developing regions, inadequate digital infrastructure and limited farmer training hinder scalability. Thus, a key global lesson is that the digital divide in agriculture must be addressed through inclusive capacity-building programs, public-private partnerships, and adaptive policy design.

Building upon the theoretical framework that highlights the transformative role of digital technologies in agriculture, the following section explores how the adoption of artificial intelligence (AI) presents significant prospects across economic, environmental, social, and technological dimensions.

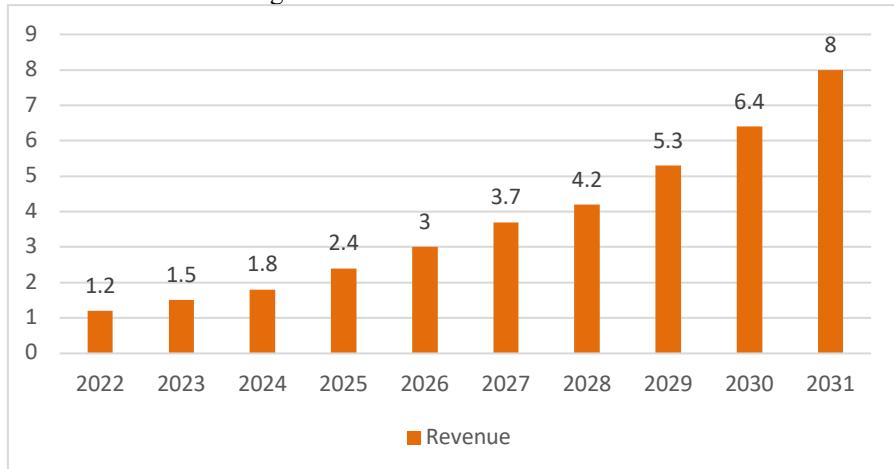
Economic Prospects. The deployment of AI in agriculture offers the potential to increase operational efficiency and reduce costs. For example, using predictive analytics and real-time data processing enable farmers to optimize inputs and reduce waste, thereby boosting productivity and profitability. According to Precedence research, the global market for AI in agriculture is projected to reach US\$16.92 billion by 2034, driven by technological advancements, growing agritech startups, and data-driven decision-making (Precedence Research, 2024).



Picture 2. Artificial intelligence in Agriculture market size 2023 to 2034 (USD Billion dollars)

Source: Precedence research

This consistent upward trend in the AI agriculture market highlights not only technological adoption but also the broader economic transformation occurring in the agricultural sector. As artificial intelligence becomes increasingly integrated into farming operations, its impact extends beyond productivity gains—it reshapes the overall revenue structure of the global agriculture market. To illustrate this interconnection, the following diagram presents the dynamics of agricultural market revenue over the same period, reflecting how digital transformation and AI-driven innovations contribute to sustained economic growth in the sector.



Picture 3. Global Artificial Intelligence in Agriculture market revenue (2022 to 2031, USD billion dollars)

Source: Market.us scoop

As illustrated in Picture 2, the global artificial intelligence (AI) in agriculture market revenue demonstrates a steady upward trajectory from 2022 to 2031. According to Market.us Scoop (2024), the revenue is expected to rise from USD 1.2 billion in 2022 to USD 8 billion by 2031, reflecting growing investment in AI-driven solutions such as precision farming, crop monitoring, and predictive analytics. This significant expansion underscores the increasing integration of digital technologies in agriculture and highlights AI's role as a catalyst for sustainable productivity and profitability within the sector.

The rise of AgriTech startups, automation of labor-intensive tasks, and the creation of new employment opportunities in related service sectors also characterise this economic shift. Nonetheless, it must be noted that the economic benefit may be uneven: smallholders in regions with limited capacity may struggle to capture the gains without supportive infrastructure and financing.

Environmental Prospects. AI-enabled agriculture presents an important avenue for environmental sustainability. Through precision farming tools, resource use can be tightly controlled, thereby reducing water, fertilizer and energy consumption. One review emphasises that AI and precision technologies can optimize resource use and reduce waste, aligning agriculture with sustainability goals (Chen et al., 2025, p. 5). For example, sensor-based irrigation systems have achieved substantial reductions in water use in some field trials. These advances suggest a pathway to lower greenhouse gas emissions and reduced environmental externalities from farming operations. However, the counter-point is that the production, maintenance and disposal of digital/robotic hardware also carry embodied environmental and energy costs—which must be integrated into any sustainability assessment.

Social Prospects. From a social perspective, AI in agriculture can empower rural communities by providing farmers with real-time information, advisory services and connectivity to markets. A recent review notes that digital agriculture technologies “empower farmers and rural actors” by offering decision-making tools and improving access to data (Frontiers, 2024, p. 3). Mobile platforms and sensor-driven apps can help smallholder farmers monitor their fields,

respond to pests and coordinate logistics—contributing to improved food distribution systems and stronger rural livelihoods. Yet, the social potential is tempered by the digital divide: farmers without access to skills, devices or connectivity risk being excluded from these benefits.

Technological Prospects. Technologically, the integration of drones, IoT sensors, robotics and AI-based decision-support systems is redefining how farms operate. IoT devices collect high-frequency data, drones monitor crop health from above, and AI algorithms process this information to guide precision interventions. It is undeniable fact that automation revolutionises farming practices by reducing dependency on manual labor and enabling more accurate decision-making. The increasing affordability and sophistication of such hardware and software platforms also suggest a shift toward “Farming as a Service” models where even smaller operations can benefit. However, the risk remains that early movers with higher capital may dominate, raising concerns about equity in technology diffusion.

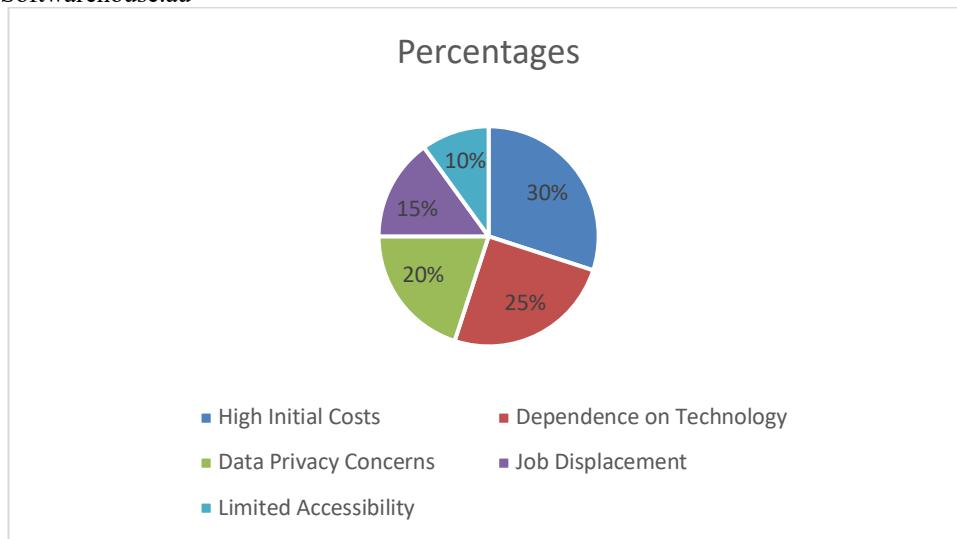
It is clear that the prospects of AI in agriculture are multi-fold: economically promising, environmentally fruitful, socially enabling, and technologically advanced. Their realization depends, however, on context-sensitive adaptation, enabling infrastructure and inclusive institutional frameworks. Having established the promising outlook for AI in agriculture, it is imperative to acknowledge the barriers that may limit or distort its effective adoption. Here is the table shows the main challenges that slows the integration of technological advancements into Agriculture:

Table 1

Disadvantages of AI in Agriculture

Disadvantage	Description	Impact on Agriculture
High Initial Costs	Expensive AI equipment and maintenance	Small farms may struggle to afford it
Dependence on Technology	Farmers rely heavily on AI for decision-making	Loss of traditional farming skills
Data Privacy Concerns	AI collects sensitive farm data	Risk of exploitation by corporations
Job Displacement	Automation reduces human labor needs	Loss of rural employment
Limited Accessibility	AI is not accessible to all regions	Digital divide between small and large farms

Source: Softwarehouse.au



Picture 4. Disadvantages of AI in Agriculture in percentage

Source: Softwarehouse.au

Building on the global experiences and trends discussed earlier, the Azerbaijani case offers an illustrative example of how developing economies are gradually integrating digital and AI-driven tools into their agricultural systems. As global evidence shows, AI-based innovation can significantly raise productivity, improve environmental sustainability, and create new rural business models when supported by robust institutional frameworks. Azerbaijan's current trajectory reflects an effort to localize these global principles within its own socio-economic and ecological context.

Agriculture remains a vital pillar of Azerbaijan's non-oil economy, employing over one-third of the labor force and serving as a key source of rural income (FAO, Digital Agriculture Country Study – Azerbaijan, 2022, p. 7). In recognition of this importance, the government's strategic vision document, Azerbaijan 2030: National Priorities for Socio-Economic Development, identifies agricultural digitalization as a central instrument to enhance food security and sustainable growth (Government of Azerbaijan, 2021, p. 19). This policy direction has been reinforced by several institutional reforms, including the creation of e-Government tools, electronic subsidy systems, and data-based monitoring for agrarian productivity.

At the heart of these reforms lies the E-Agriculture platform, launched by the Ministry of Agriculture in 2019, which integrates farm-level data, land-use registries, and subsidy applications into a single electronic system. It provides farmers with access to real-time market and weather information, aiming to replace bureaucratic processes with digital solutions (Ministry of Agriculture of Azerbaijan, Digital Agriculture Report, 2023, p. 24). Complementing this initiative, the Food and Agriculture Organization's "Digital Villages Initiative" has promoted Azerbaijan's Smart Village pilot in Aghali as a model for integrating IoT devices, drones, and data analytics into local farming operations (FAO, 2022, p. 15). This project aligns with the concept of Agriculture 4.0, creating a bridge between physical agricultural activities and intelligent digital systems.

Moreover, a joint programme between FAO and the Ministry of Agriculture in 2023 introduced digital irrigation monitoring systems in six economic regions, designed to optimize water use and crop yields (FAO, Irrigation Systems Training Report, 2023, p. 11). The application of remote sensing, GIS mapping, and AI-based yield forecasting provides a tangible example of how theoretical digital models discussed in global literature can be operationalized in practice. These initiatives demonstrate the gradual institutionalization of AI applications, data-driven farming, and precision agriculture within Azerbaijan's rural economy.

Nevertheless, significant barriers persist. According to the World Bank's Digital Transformation of Agriculture in Europe and Central Asia (2023, p. 62), Azerbaijan faces constraints related to insufficient broadband connectivity in rural areas, limited interoperability of data systems, and inadequate digital literacy among farmers. The FAO study also highlights the fragmented nature of agricultural data and the lack of standardized frameworks for AI adoption (FAO, 2022, p. 27). Such challenges reflect the global pattern identified earlier—technological advancement requires not only access to innovation but also human capital development and institutional readiness.

On the other hand, the opportunities are considerable. Azerbaijan's semi-arid climate and water scarcity issues make it particularly suitable for applying AI in precision irrigation and resource optimization. The OECD's Digital Transformation and Skills Development in Eastern Partner Countries (2023, p. 54) emphasizes that Azerbaijan possesses a young, adaptable labor force and a government-driven innovation agenda that can accelerate digital adoption in agriculture. Furthermore, the World Bank Country Partnership Framework for Azerbaijan 2025–2030 underscores the role of emerging technologies—including AI-based monitoring and smart irrigation—in promoting a greener and more competitive economy (World Bank, 2025, p. 31).

Azerbaijani case demonstrates a transition from pilot-scale projects to systemic integration of AI and digital tools in agriculture. While infrastructural and institutional gaps remain, the synergy between national strategies, international cooperation, and global technological trends places Azerbaijan in a favorable position to harness the benefits of Agriculture 4.0. Bridging this progress with policy continuity and farmer training will be crucial for turning digitalization into a sustainable transformation rather than a temporary modernization phase.

CONCLUSIONS

This study set out to explore the prospects of digital transformation and the use of Artificial Intelligence (AI) in agriculture, addressing how technological innovation can respond to the urgent challenges of food security, resource scarcity, and climate change. Through theoretical analysis and comparative evidence, the paper demonstrated that AI represents far more than a set of modern tools—it constitutes a structural shift toward data-driven, sustainable, and knowledge-intensive farming systems.

The findings indicate that AI applications—spanning precision irrigation, soil analytics, pest detection, and predictive modelling—enhance agricultural efficiency and environmental stewardship while opening new economic and social opportunities. Yet, the research also underscores that digital transformation is uneven. While advanced economies progress toward fully integrated smart-farming ecosystems, developing nations such as Azerbaijan are still building the institutional and infrastructural foundations required for broad adoption.

By linking global experience to the Azerbaijani context, the study concludes that realizing AI's full potential demands coherent national strategies, investment in human capital, and multi-sector collaboration. The effective fusion of technology, policy, and education can turn agriculture into a driver of innovation-led sustainable growth, fulfilling both economic and ecological goals in the era of digital transformation.

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