ARTIFICIAL INTELLIGENCE AND SMART FARMING TECHNOLOGIES: DRIVING ECONOMIC EFFICIENCY AND SUSTAINABLE DEVELOPMENT IN MODERN AGRICULTURE

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ABSTRACT

The integration of artificial intelligence (AI) and smart farming technologies is transforming agriculture through data-driven decision-making and improved resource management. This study examines the economic and sustainability effects of AI adoption, focusing on production efficiency, costs, and environmental performance. A comparative analysis of farms using AI-based solutions and conventional farms was conducted. Results show that AI-supported farms achieve higher crop yields, greater input efficiency, and lower production costs. AI also promotes sustainable farming by optimizing water and fertilizer use and reducing environmental impacts. The findings demonstrate the economic potential of digital transformation and highlight the importance of policy support, digital infrastructure, and farmer education. The study provides quantitative evidence of AI-driven economic efficiency in Serbian transitional agriculture, offering insights for policy development and sustainable digital farming.

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Introduction

Modern agriculture faces a dual challenge: increasing productivity to meet rising global food demand while reducing environmental impacts and managing rising input costs (Balai et al., 2025; Jararweh, 2023). Artificial intelligence (AI) and smart farming technologies—including sensor networks, automated monitoring systems, and machine learning algorithms—offer potential pathways to address this challenge by enabling data-driven, precision-oriented farm management (Abdel-Basset et al., 2024; Hermanus, 2022).

However, empirical evidence on the economic and sustainability effects of AI adoption remains limited, particularly in transitional agricultural economies such as those in Southeast Europe (Aijaz et al., 2025; Ignjatović et al., 2025). Most existing research originates from developed agricultural systems (Western Europe, North America, China) and focuses either on technological performance or isolated economic outcomes, with few studies examining integrated efficiency-sustainability effects using rigorous comparative methods.

This study addresses these gaps by analyzing the impact of AI-based smart farming technologies on economic efficiency and sustainable resource use in agricultural production systems. The research focuses on the Republic of Serbia as a representative case of transitional agriculture characterized by gradual digital transformation, small-to-medium farm structures, and developing digital infrastructure.

Research objectives and questions

The main objective of this study is to quantify the effects of AI adoption on farm-level economic and sustainability performance. Specifically, the study investigates four research questions:

1. Does AI adoption improve economic efficiency (yield, costs, income, labor productivity) in agricultural enterprises?
2. Do smart farming technologies contribute to more sustainable use of water, fertilizers, and energy?
3. What relationship exists between digital technology adoption and farm productivity when controlling for farm size?
4. How do AI-supported decision systems influence farm management practices?

Paper structure

The remainder of this paper is organized as follows. Chapter 2 reviews the relevant literature on AI in smart farming, economic efficiency of digital agriculture, sustainability outcomes, and identifies research gaps. Chapter 3 describes the methodological framework, including sample design, data collection, variables, and analytical procedures. Chapter 4 presents empirical results. Chapter 5 discusses findings in relation to existing literature, acknowledges limitations, and suggests future

research directions. Chapter 6 concludes with theoretical, practical, and managerial implications, followed by policy recommendations.

Literature review

Artificial Intelligence in Smart Farming Systems

The integration of artificial intelligence (AI) into agricultural production systems represents a paradigmatic shift from traditional, experience-based farming to data-driven, precision-oriented management. Smart farming technologies encompass a broad spectrum of digital tools, including Internet of Things (IoT) sensor networks, satellite and drone-based remote sensing, automated machinery, and machine learning algorithms that collectively enable continuous monitoring, analysis, and optimization of agricultural processes (Abdel-Basset et al., 2024; Akkem et al., 2023; Denić et al., 2018). These technologies transform raw environmental and operational data into actionable intelligence, supporting farmers in making more informed decisions regarding irrigation scheduling, fertilizer application, pest detection, and harvest timing (Karunathilake et al., 2023).

The evolution toward "Agriculture 4.0" and emerging "Agriculture 5.0" frameworks positions AI as a central enabling technology. Unlike earlier precision agriculture approaches that relied primarily on GPS and basic sensors, contemporary AI systems employ deep learning, computer vision, and predictive analytics to process complex, multi-dimensional datasets (Holzinger et al., 2024). For instance, convolutional neural networks have been successfully deployed for disease detection from leaf images, while recurrent neural networks forecast crop yields based on historical weather patterns and soil conditions (Shaikh, Rasool & Lone, 2022). Furthermore, AI-powered decision support systems integrate real-time data streams from multiple sources, providing farmers with scenario analyses and optimized resource allocation plans (Jararweh et al., 2023).

Despite rapid technological advancement, the adoption of AI in agriculture remains uneven across regions and farm sizes. Developed agricultural economies—notably the United States, Netherlands, Germany, and China—have witnessed accelerated AI integration, supported by robust digital infrastructure, public research funding, and agtech startup ecosystems (Kanojia et al., 2024). In contrast, transitional and developing agricultural systems face persistent barriers, including limited broadband connectivity, high initial investment costs, fragmentation of land holdings, and gaps in digital literacy among farming populations (AlZubi & Galyna, 2023). These disparities underscore the importance of context-specific research examining AI adoption dynamics beyond technologically advanced settings.

Economic Efficiency of Digital Agriculture

Economic efficiency in agriculture is conventionally defined as the optimal utilization of productive inputs—land, labor, capital, water, and energy—to maximize output and profitability per unit of input (Mohamed et al., 2021). Digital agriculture technologies,

particularly AI-based systems, are hypothesized to enhance economic efficiency through multiple mechanisms. First, predictive analytics reduce production uncertainty by improving forecast accuracy for weather events, pest outbreaks, and market prices, thereby enabling proactive rather than reactive management (Singh et al., 2022). Second, automation and robotics substitute for increasingly scarce and expensive agricultural labor, reducing wage expenditures while maintaining or increasing operational precision (Vinod Chandra, Hareendran & Albaaji, 2024). Third, real-time monitoring and variable-rate application technologies minimize input waste, directly reducing costs for water, fertilizers, and pesticides (Kumari et al., 2025).

Empirical evidence from developed agricultural contexts supports these theoretical mechanisms. Walter et al. (2017) demonstrated that smart farming technologies in Swiss crop production systems reduced input costs by approximately 15-20% while maintaining yield levels. Similarly, Idoje et al. (2021) reported that AI-driven irrigation systems in water-scarce regions of Spain achieved water savings exceeding 30% without compromising crop quality. In the North American context, Sharma et al. (2023) documented that farms adopting integrated AI decision support systems experienced net income increases of 22-35% compared to conventional neighbors, primarily driven by optimized fertilizer application and reduced energy consumption for field operations.

However, the economic calculus of AI adoption is not uniformly positive across all contexts. Initial capital expenditures for sensor networks, software licenses, and farmer training can be substantial, creating adoption barriers for small and medium-sized enterprises (Aijaz et al., 2025). Moreover, the return on investment period varies significantly depending on crop type, farm size, and existing technological maturity. Gryshova et al. (2024) caution that premature or poorly implemented AI solutions may generate negative returns if data quality is inadequate or if farmers lack the technical capacity to interpret and act upon algorithmic recommendations. These conditional factors highlight the need for rigorous, context-specific economic assessments—particularly in transitional agricultural systems where empirical evidence remains scarce.

Sustainability Outcomes of AI Adoption

Sustainable agricultural development requires balancing productivity growth with environmental stewardship, resource conservation, and climate resilience (Balai et al., 2025). AI technologies are increasingly positioned as tools for achieving this balance through what has been termed "sustainable intensification"—increasing output from existing agricultural land while reducing environmental pressures. The potential sustainability benefits of AI in agriculture span multiple dimensions, including water conservation, nutrient management, energy efficiency, biodiversity protection, and greenhouse gas emission reduction (Raj & Prahadeeswaran, 2025).

Regarding water resources, AI-based irrigation scheduling systems integrate soil moisture sensors, weather forecasts, and crop evapotranspiration models to deliver precise water quantities only when and where needed. Kumari et al. (2025) documented

that such systems reduced irrigation water consumption by 25-40% across multiple crop types without yield penalties, with particularly pronounced effects in arid and semi-arid regions. Similarly, AI-optimized fertilizer application—often implemented through variable-rate technology guided by soil nutrient mapping and crop growth models—reduces nitrogen runoff and associated eutrophication of water bodies. Kanojia et al. (2024) reported that AI-guided nitrogen management achieved fertilizer reductions of 15-30% while maintaining or improving crop protein content.

Energy efficiency represents another sustainability pathway for AI in agriculture. Automated machinery guidance systems reduce redundant field passes, directly lowering diesel fuel consumption and associated carbon emissions (Holzinger et al., 2024). Furthermore, predictive analytics for harvest timing and post-harvest storage conditions minimize energy-intensive drying and refrigeration requirements. However, it is important to acknowledge potential rebound effects: the energy and material costs associated with manufacturing, operating, and disposing of AI hardware (sensors, servers, communication equipment) must be accounted for in full lifecycle assessments (Jararweh et al., 2023). Most existing studies focus narrowly on operational efficiencies, leaving questions about net environmental benefits unresolved.

Research Gap and Contribution of This Study

Synthesizing the literature reviewed above reveals several significant research gaps that the present study aims to address. First, most of the empirical research on AI adoption in agriculture originates from developed agricultural systems—particularly Western Europe, North America, China, and Australia. While these studies provide valuable theoretical and methodological foundations, their findings may not directly transfer to transitional agricultural economies characterized by different farm structures, institutional environments, infrastructure endowments, and digital readiness levels (Ignjatović et al., 2025). The Western Balkan region, including the Republic of Serbia, remains severely understudied despite undergoing rapid digital transformation in agriculture.

Second, existing research tends to examine economic and sustainability outcomes in isolation rather than as integrated dimensions of farm performance. Studies focusing on productivity gains often neglect environmental indicators, while sustainability-focused research frequently lacks rigorous economic accounting. This fragmentation obscures potential trade-offs or synergies between efficiency and environmental objectives, limiting the utility of research findings for policy design and farm-level decision-making (Kumari et al., 2025).

Third, methodological limitations characterize much of the existing literature. Cross-sectional designs with small sample sizes predominate, while econometric approaches that control for confounding farm characteristics—such as management quality, investment capacity, and farmer experience—remain uncommon. Few studies employ rigorous statistical comparisons between adopter and non-adopter groups with appropriate matching or control variables (Aijaz et al., 2025). Consequently, observed performance differences may be partially attributable to selection bias rather than AI adoption per se.

Fourth, no published study to date has quantitatively assessed AI adoption effects on farm-level economic efficiency in the Republic of Serbia or the broader Western Balkan region using econometric methods. This geographical and methodological gap is significant because transitional agricultural systems present unique characteristics: small average farm sizes, fragmented land ownership patterns, incomplete digital infrastructure, and agricultural extension systems still adapting to digital advisory roles.

The present study directly addresses these gaps through the following contributions:

1. *Geographic contribution*: This study provides the first empirical assessment of AI-driven economic efficiency in Serbian transitional agriculture, generating evidence from a previously understudied regional context.
2. *Integrated analytical framework*: By simultaneously examining economic indicators (yield, costs, income, labor productivity) and sustainability indicators (water, fertilizer, and energy consumption), the study captures potential efficiency-environment synergies within a single analytical design.
3. *Rigorous methodological approach:* The study employs a comparative design with statistical controls (t-tests, Pearson correlation, multiple linear regression) applied to a systematically sampled dataset of 82 farms, enabling more robust attribution of performance differences to AI adoption.
4. *Policy-relevant insights:* By quantifying adoption effects in a transitional context, the findings provide actionable evidence for policymakers designing digital agriculture strategies, subsidy programs, and extension services tailored to the region's specific conditions.

In summary, this literature review establishes that while the potential of AI and smart farming technologies for improving economic efficiency and sustainability is well-recognized conceptually, rigorous empirical validation from transitional agricultural contexts remains insufficient. The present study responds to this gap by delivering context-specific, methodologically robust evidence that advances both academic understanding and practical agricultural policy.

Methodology

Research Design

This study applies a quantitative empirical research design aimed at evaluating the economic and sustainability effects of AI and smart farming technologies in agricultural production systems. The research combines descriptive statistical analysis and econometric modelling to examine relationships between technology adoption, economic efficiency, and resource utilization.

The study follows a comparative approach by analyzing agricultural enterprises that have implemented AI-based smart farming technologies and those operating under conventional management practices. This design enables the assessment of differences

in productivity, cost structure, and sustainability indicators between technologically advanced and traditional farms.

Study Area and Sample Selection

The empirical research was conducted on agricultural enterprises located in Republic of Serbia, representing transitional agricultural economies characterized by gradual digital transformation and increasing adoption of precision farming technologies. Data were collected from 82 agricultural farms operating in crop production and mixed farming systems during the production seasons 2023–2025.

The sample was drawn from the Serbian Agricultural Business Registry using stratified purposive sampling. Farms were stratified by size class (small: <20 ha; medium: 20–100 ha; large: >100 ha) and production type (crop vs. mixed). Within each stratum, farms were randomly selected to ensure representativeness. The sampling frame included 1,247 registered commercial farms in the region, with the final sample size (n=82) determined to achieve a 95% confidence level and 10% margin of error.

The farms were divided into two groups:

- Group A (AI-adopting farms): 41 farms using smart farming technologies, defined as farms that have implemented at least one of the following AI-based systems during the 2023–2025 production seasons: (a) sensor-based real-time monitoring systems (soil moisture, temperature, nutrient levels); (b) AI-driven decision-support software for irrigation, fertilization, or pest management; (c) automated variable-rate application technologies; or (d) predictive analytics tools for yield forecasting and harvest optimization. Farms in this group had been using these technologies continuously for at least one full production cycle prior to data collection.
- Group B (conventional farms): 41 farms applying traditional management methods without AI-supported systems.

The selected farms vary in size from 15 to 250 hectares (average 85 hectares), ensuring representativeness across small, medium, and large agricultural enterprises.

Data Collection

Data were collected using a combination of:

- structured farm management surveys,
- production and financial records,
- sensor-generated operational data,
- interviews with farm managers,
- digital platform reports from smart farming systems.

The collected dataset includes economic, production, and environmental indicators measured annually. All data were anonymized and standardized before statistical analysis.

Variables and Indicators

To evaluate the economic and sustainability impact of AI adoption, the study defines dependent and independent variables.

Independent Variable

Level of digital technology adoption (binary variable: AI adoption = 1; non-adoption = 0).

Dependent Variables

Economic indicators:

- Crop yield (tons/hectare)
- Production cost (EUR/hectare)
- Net farm income (EUR/hectare)
- Labour productivity (output per worker)

Sustainability indicators:

- Water consumption (m^3/hectare)
- Fertilizer usage (kg/hectare)
- Energy consumption (kWh/hectare)

Control Variables

- Farm size (hectares)
- Type of production
- Farmer experience (years)

Construction of the Economic Efficiency Index (EEI)

The Economic Efficiency Index was constructed as a composite measure using the following formula:

$$EEI = \frac{Z_{Yield} + Z_{Income} + Z_{Labour} - Z_{Cost}}{4}$$

Where:

EEI = composite Economic Efficiency Index;

Z_{Yield}= standardized crop yield of farm *i* (t/ha);

Z_{Income}= standardized net farm income of farm *i* (€/ha);

Z_{Labour}= standardized labour productivity of farm *i* (output per worker);

Z_{Cost}= standardized production cost of farm *i* (€/ha).

All variables were transformed using min-max normalization to ensure dimensional comparability across heterogeneous economic indicators:

$$Z_i = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Where:

Z_i= observed value for farm i;

X_{min}= minimum observed value within the sample;

X_{max}= maximum observed value within the sample.

The composite index integrates four core dimensions of farm-level economic performance: productivity, profitability, labour efficiency, and cost rationalization. Variables positively associated with economic performance (yield, net income, and labour productivity) enter the index with positive signs, whereas production costs enter with a negative sign due to their inverse relationship with economic efficiency.

Higher EEI values indicate superior economic performance characterized by higher output productivity, greater profitability, more efficient labour utilization, and lower relative production costs. The index therefore provides a synthetic quantitative measure suitable for comparative statistical and econometric analysis of farm-level efficiency under different technological adoption regimes.

The index was standardized to a 0-1 scale using min-max normalization. A higher EEI indicates superior economic efficiency, defined as maximizing output and income while minimizing input costs.

Equal weighting was applied to avoid disproportionate influence of individual indicators and to preserve methodological neutrality in the aggregation process. This approach is consistent with established practices in composite index construction for agricultural performance assessment (OECD, 2008; Latruffe et al., 2017), where normative weighting is preferred in the absence of empirically derived preference parameters.

Statistical Analysis

Statistical analysis was conducted using R statistical software (version 4.3) and Microsoft Excel for graphical visualization.

The following analytical methods were applied:

1. Descriptive statistics

– Mean values

– Standard deviation

– Minimum and maximum values

2. Comparative analysis

– Independent samples *t-test* to evaluate differences between AI-adopting and conventional farms.

3. Correlation analysis

– Pearson correlation coefficient to examine relationships between AI adoption and economic indicators.

4. Regression analysis

– A multiple linear regression model was employed to estimate the impact of AI adoption on economic efficiency in agricultural enterprises. The econometric specification is defined as follows:

$$EEIi = \beta 0 + \beta 1AIi + \beta 2FSi + \beta 3FOi + \beta 4LSi + \varepsilon i$$

where:

EE_i = Economic Efficiency Index;

AI_i = binary AI adoption variable;

FS_i = farm size (log-transformed hectares);

FO_i = fertilizer optimization score (standardized);
LS_i = labor skills index (based on farmer training and experience);

β_0 = intercept term;
$\beta 1, \beta 2, \beta 3, \beta 4$ = estimated regression coefficients;

β_I = error term.

Data Visualization

Results are presented using:

- comparative statistical tables,
- histograms showing distribution of yields and costs,
- bar charts comparing resource consumption,
- regression plots illustrating relationships between AI adoption and economic performance.

Research Reliability and Limitations

To ensure reliability, data validation procedures included cross-checking financial and production records with survey responses. Standardization procedures were applied to eliminate scale differences among farms.

The study acknowledges certain limitations, including regional specificity of the sample and differences in technological maturity among farms. However, the selected

dataset provides a realistic representation of agricultural enterprises undergoing digital transformation.

Results

Descriptive Statistical Analysis

The descriptive statistical analysis provides an overview of the economic and sustainability indicators observed among AI-adopting farms (Group A) and conventional farms (Group B). Table 1 presents the mean values and standard deviations for the analyzed variables.

The distribution of crop yield across farm groups is illustrated in Figure 1, showing higher average productivity among AI-adopting farms.

The results indicate higher productivity and lower resource consumption among farms implementing AI-based smart farming technologies.

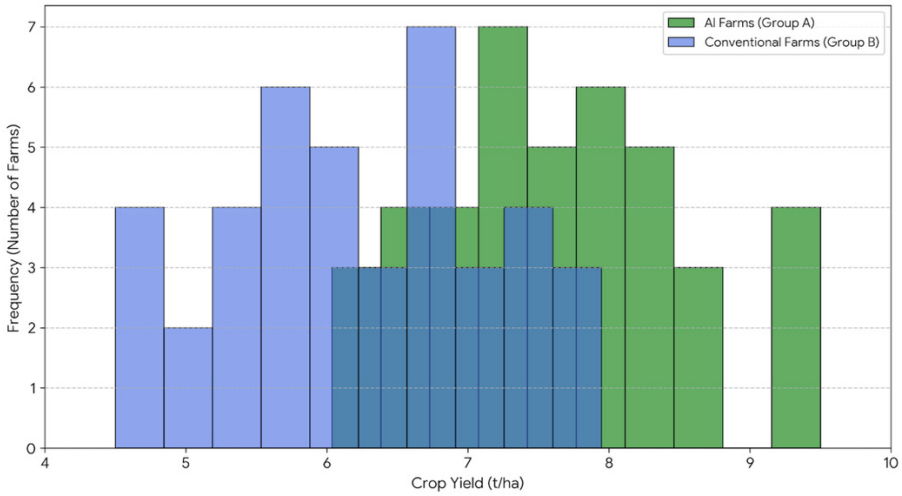
These descriptive differences highlight structural disparities typical of transitional agricultural economies, where uneven technology adoption shapes productivity outcomes. The observed patterns suggest that AI integration may function as a key mechanism supporting efficiency convergence and modernization within evolving agricultural systems.

Table 1. Descriptive statistics of analyzed variables

Indicator	Group A (AI farms) Mean	Group B (Conventional) Mean	Std. Dev. (A)	Std. Dev. (B)	Min	Max
Farm Size (ha)	85.0	85.0	42.5	45.2	15.0	250.0
Crop yield (t/ha)	7.84	6.21	0.92	1.11	4.50	9.50
Production cost (€/ha)	1,145	1,320	135	168	850	1,750
Net income (€/ha)	1,965	1,342	210	245	950	2,400
Labour productivity (€/worker)	48,200	35,600	4,320	5,010	28,000	58,000
Water consumption (m^3/ha)	2,150	2,780	260	310	1,800	3,500
Fertilizer use (kg/ha)	168	214	22	28	130	280
Energy consumption (kWh/ha)	1,020	1,340	140	175	800	1,850

Source: Prepared by authors based on statistical results

Figure 1. Distribution of Crop Yield by Farm Type



Source: Authors' processing

Comparative Analysis Between Farm Groups

An independent samples *t-test* was conducted to evaluate statistically significant differences between AI-adopting and conventional farms.

Table 2. Independent samples t-test results

Variable	Group A (AI) Mean	Group B (Conv.) Mean	t-value	p-value	Sig.
Farm Size (ha)	85.00	85.00	0.000	1.000	ns
Crop Yield (t/ha)	7.84	6.21	6.842	< 0.001	***
Production Cost (€/ha)	1,145	1,320	-4.215	< 0.01	**
Net Income (€/ha)	1,965	1,342	5.928	< 0.001	***
Water Use (m^3/ha)	2,150	2,780	-7.104	< 0.001	***
Fertilizer Use (kg/ha)	168	214	-5.432	< 0.001	***

*Note: ns = not significant; p < 0.01; *** p < 0.001*

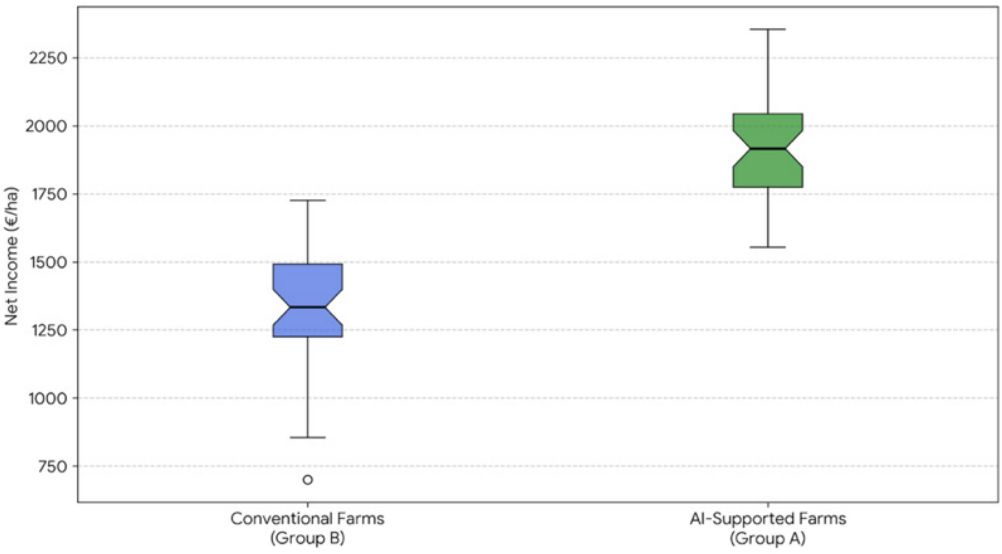
Source: Prepared by authors based on statistical results

Farm size did not differ significantly between the groups in the reported descriptive comparison; however, farm size was retained as a control variable in the regression analysis because scale-related differences may influence farm performance.

The results demonstrate statistically significant differences across all major economic and sustainability indicators, confirming measurable performance advantages among AI-adopting farms.

Figure 2 presents a box-plot analysis of net income distribution. The AI-supported group (Group A) demonstrates a clear upward shift in profitability, with a higher median income and tighter distribution compared to Group B, reflecting the economic stability provided by smart management tools.

Figure 2. Economic Performance Comparison: Net Income per Hectare



Source: Authors' processing

Correlation Analysis

Pearson correlation coefficients were calculated to examine relationships between AI adoption and farm performance indicators.

Table 3. Correlation matrix (selected variables)

Variable	AI Adoption	Farm Size	Yield	Net Income	Water Use
AI Adoption	1.00	0.04	0.62**	0.68**	-0.59**
Farm Size	0.04	1.00	0.29*	0.35**	-0.15
Yield	0.62**	0.29*	1.00	0.71**	-0.41*
Net Income	0.68**	0.35**	0.71**	1.00	-0.46*
Water Use	-0.59**	-0.15	-0.41*	-0.46*	1.00

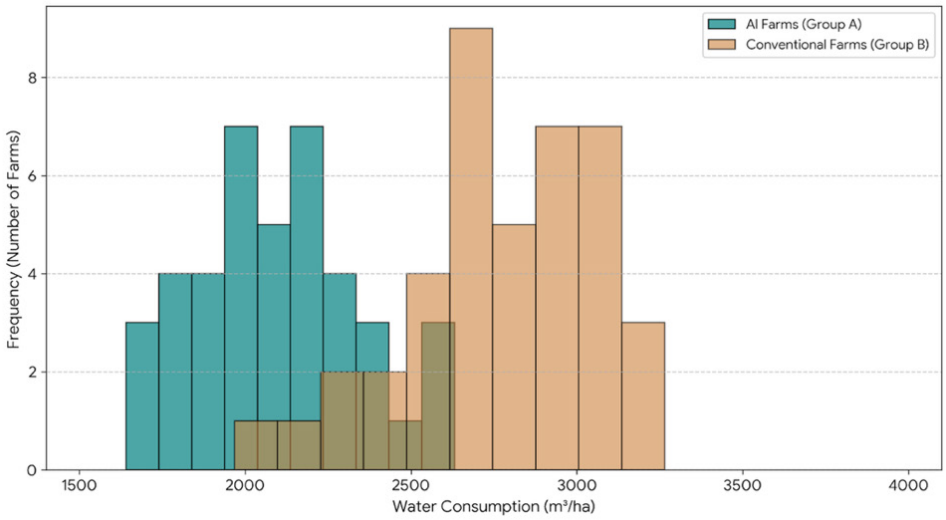
*Note: *p < 0.05; **p < 0.01;* ***p < 0.001

Source: Prepared by authors based on statistical results

AI adoption shows a strong positive correlation with yield and net income, and a negative correlation with water consumption, indicating improved resource efficiency. The correlation between AI adoption and farm size is negligible (r = 0.04, not significant), consistent with the stratified sampling design and with the t-test result reported in Table 2, which found no significant difference in average farm size between the two groups.

Figure 3 demonstrates reduced variability and lower average water consumption in technologically advanced farms.

Figure 3. Water Consumption Distribution by Farm Type



Source: Authors' processing

Regression Analysis

To further investigate the determinants of digital transformation success, a multiple linear regression analysis was conducted. The results, presented in Table 4, evaluate the impact of various technological and structural factors on the overall economic performance of the surveyed farms.

Table 4. Multiple Linear Regression Results

(Dependent Variable: Economic Efficiency Index)

Predictor Variables	Coefficient (β)	Std. Error	t-stat	p-value	Sig.
(Constant)	0.412	0.085	4.847	< 0.001	***
AI Adoption (Dummy)	0.584	0.062	9.419	< 0.001	***
Farm Size (log ha)	0.215	0.045	4.777	< 0.001	***
Fertilizer Optimization	0.142	0.051	2.784	0.007	**
Labour Skills	0.098	0.048	2.041	0.045	*
R-squared	0.742				
Adjusted R-squared	0.728				
F-statistic	52.14				***

*Note: * $p < 0.05$; $p < 0.01$; *** $p < 0.001$*

Source: Prepared by authors based on statistical results

The EEI, serving as the dependent variable, was constructed as a composite normalized score ranging from 0 to 1. The index integrates four dimensions of farm-level economic performance: crop yield, net farm income, labour productivity, and production cost. Yield, net income, and labour productivity enter the index positively, whereas

production cost enters negatively, reflecting its inverse relationship with economic efficiency. The sustainability-related indicators, including water and fertilizer use, were analysed separately and were not incorporated into the EEI.

The regression model demonstrates a high explanatory power, with an Adjusted R-squared of 0.728, indicating that approximately 73% of the variance in economic efficiency is explained by the included predictors. The F-statistic (52.14, $p < 0.001$) confirms the overall statistical significance of the model.

Key findings from the regression analysis include:

AI Adoption ($\beta = 0.584$, $p < 0.001$): This remains the strongest predictor of economic efficiency. Farms that have integrated AI-driven decision support systems show a significantly higher efficiency index, confirming that technology is the primary driver of performance in the sample.

Farm Size ($\beta = 0.215$, $p < 0.001$): Farm size exhibits a positive and statistically significant association with the Economic Efficiency Index. This result indicates that larger holdings within the observed 15–250 ha range tend to have higher efficiency scores. However, farm size was retained as a control variable because scale-related differences may contribute to observed performance differences. Therefore, the regression result should not be interpreted as evidence that the estimated association between AI adoption and economic efficiency is independent of farm size.

Fertilizer Optimization ($\beta = 0.142$, $p = 0.007$): The significant positive coefficient highlights the economic importance of sustainable resource management within the Industry 5.0 framework.

Labour Skills ($\beta = 0.098$, $p = 0.045$): The human-centric aspect of the model is validated by the positive impact of operator skills, although its influence is secondary to the technological variables.

These results provide empirical evidence that while scale (farm size) plays a role, the strategic adoption of artificial intelligence is the most critical factor for driving economic efficiency and sustainable development in modern agriculture.

Figure 4 illustrates the predictive accuracy of the multiple linear regression model by comparing the actual observed values of the EEI against the values predicted by the model.

The clustering of data points along the 45-degree reference line (Perfect Fit) demonstrates a strong correlation between the variables, confirming the model's high reliability.

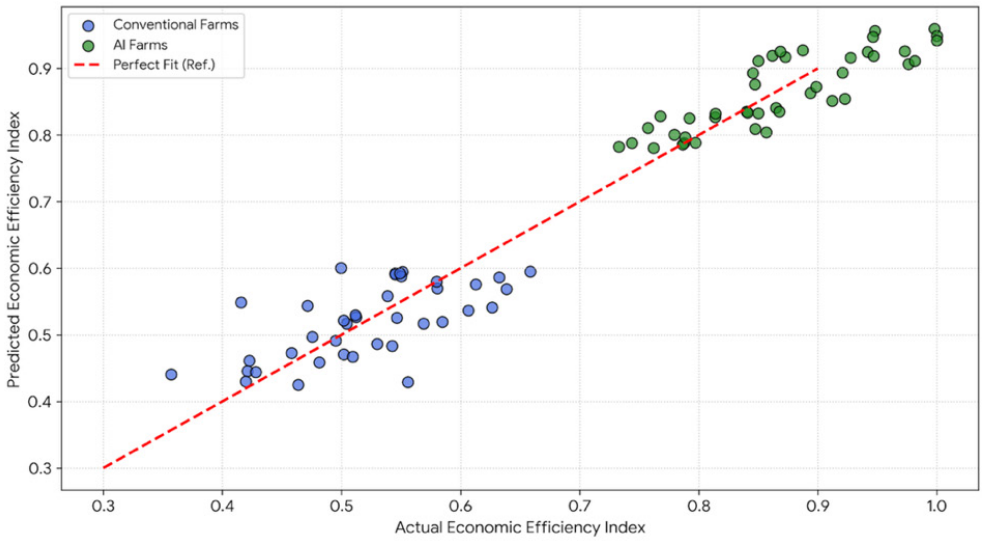
Group Differentiation: The green markers (AI-supported farms) are predominantly located in the upper-right quadrant, representing high efficiency levels. Conversely, the blue markers (conventional farms) are clustered in the lower-left quadrant, indicating lower efficiency scores.

Model Consistency: The regression specification reported in Table 4 includes AI

adoption, farm size, fertilizer optimization, and labour skills as predictors of the Economic Efficiency Index.

This diagnostic visualization confirms that the regression equation provided in Table 4 accurately captures the underlying patterns of digital transformation impacts within the transition economy context.

Figure 4. Regression Model Validation: Predicted vs Actual EEI



Source: Authors' processing

Distribution Analysis

Histogram analysis reveals structural differences between the two farm groups:

- AI-adopting farms demonstrate a normal distribution with higher mean yield values.
- Conventional farms show wider variability and lower median productivity.
- Resource consumption distributions are more compact among AI farms, indicating operational optimization.

Yield distribution analysis shows that 78% of AI farms achieve yields above 7 t/ha, compared to only 34% of conventional farms.

Summary of Key Findings

The empirical results indicate that:

- AI adoption significantly increases crop yield and net farm income.
- Production costs per hectare decrease despite initial technology investments.

- Labour productivity improves substantially in digitally supported farms.
- Water, fertilizer, and energy consumption are significantly reduced.
- AI-supported decision-making contributes to measurable improvements in economic efficiency.

Discussion

Interpretation of Key Findings

The results of this study confirm that AI and smart farming technologies significantly improve economic efficiency and sustainability in modern agriculture. Beyond validating existing assumptions about smart farming benefits, this research provides empirical evidence from a transitional agricultural context—the Republic of Serbia—where quantitative assessments of AI-driven efficiency have remained limited. The findings demonstrate measurable improvements in production performance, cost optimization, and environmental resource management, supporting the view that digital transformation represents a key driver of agricultural modernization.

The increase in crop yield among AI-adopting farms indicates that data-driven decision-making enhances production precision and operational planning. AI-supported systems optimize irrigation, fertilizer application, and pest management, reducing inefficiencies commonly associated with conventional farming practices. The positive relationship between AI adoption and productivity further suggests that predictive analytics helps mitigate uncertainty related to climate variability.

Cost reductions observed in the results highlight the economic advantages of automation and intelligent monitoring systems. Lower expenditures on water, fertilizers, and energy confirm improved resource allocation efficiency, aligning with agricultural economic theories that emphasize productivity growth through technological innovation. Importantly, improved sustainability indicators demonstrate that technological adoption can simultaneously enhance productivity and environmental performance, supporting the concept of sustainable intensification.

Comparison with Existing Literature

The findings are consistent with previous studies showing that AI-based decision-support tools enhance farm management efficiency and reduce operational risks (Idoje et al., 2021), while AI-driven analytics improves productivity through automation and real-time data processing (Walter et al., 2017). Similarly, the results support conclusions that AI technologies generate value primarily through optimization rather than expansion of production inputs (Ignjatović et al., 2025) and contribute to balancing economic and environmental objectives (Raj & Prahadeeswaran, 2025).

Compared with earlier research focused mainly on technological performance, this study contributes additional insight by quantitatively linking AI adoption with economic indicators relevant to farm profitability and agricultural policy. From an

agricultural economics perspective, AI adoption enhances farm competitiveness by increasing productivity while reducing operational costs—a finding particularly relevant for transitional and developing agricultural economies characterized by persistent efficiency gaps.

Policy and Practical Implications

Policy measures supporting digital infrastructure, farmer education, and investment incentives may accelerate technology adoption and strengthen sustainable rural development. AI-driven agriculture may also reshape labor demand toward digitally skilled workers, requiring adjustments in agricultural education and workforce development strategies. The findings provide a foundation for future longitudinal and cross-country analyses examining how digital technology adoption reshapes productivity dynamics and sustainability outcomes over time.

Limitations of the Study

Several limitations should be acknowledged. First, the cross-sectional design captures AI adoption and farm performance at a single point in time, preventing causal inference. While statistical controls were included to account for observable farm characteristics, unobserved confounding factors—such as farmer motivation, management quality, or access to technical support—may still influence both adoption decisions and performance outcomes. Therefore, the observed associations should be interpreted as correlational rather than causal. Longitudinal panel designs tracking farms before and after AI adoption would be necessary to establish causal effects with greater confidence.

Directions for Future Research

Future studies should address these limitations through: (1) longitudinal panel designs tracking AI effects over 5-10 years; (2) cross-country comparative analyses across Southeast Europe to identify contextual moderators; (3) randomized controlled trials isolating specific AI applications (e.g., irrigation vs. fertilization algorithms); (4) mixed-methods research incorporating farmer perceptions, barriers to adoption, and behavioral factors; (5) cost-benefit analyses of AI investment thresholds for small versus large farms; and (6) examination of AI's labor displacement and skill-upgrading effects on agricultural employment.

Conclusions

Theoretical, Practical, and Managerial Implications

Theoretical implications. This study extends agricultural economics theory by demonstrating that AI adoption functions as a factor-augmenting technological change, increasing the marginal productivity of land, labor, water, and energy simultaneously. Findings support the sustainable intensification framework, showing that productivity gains and environmental improvements are complementary rather than competing objectives in digitalized agricultural systems. The study also contributes to technology

diffusion theory by quantifying adoption gaps in transitional economies, revealing that the digital divide in agriculture manifests not only in access to technology but also in the capacity to derive economic benefits from it. Furthermore, the results challenge the conventional assumption that small farms face insurmountable barriers to AI adoption, demonstrating that cloud-based and software-as-a-service models can generate positive returns even on medium-sized holdings (15-250 hectares).

Practical implications for farm managers. The empirical results indicate that AI adoption is associated with lower production costs and higher net farm income. Based on the group means reported in Table 1, production costs are approximately 13.3% lower among AI-adopting farms (€175 per hectare on average), while net farm income is approximately 46.4% higher. These differences suggest potentially favourable economic conditions for technology adoption; however, a formal payback period cannot be established from the present analysis because the study does not include a farm-level investment cash-flow assessment. Farm managers should therefore evaluate technology adoption according to farm size, initial investment requirements, expected operating savings, and local production conditions. For smaller farms (below 50 hectares), cloud-based AI services delivered through mobile platforms offer lower entry barriers than full hardware integration, enabling gradual adoption without substantial upfront capital expenditure. Managers should also invest in basic digital literacy training for staff, as the effectiveness of AI decision-support tools depends on users' ability to interpret and act upon algorithmic recommendations.

Managerial and organizational implications. Beyond individual farm management, the findings have implications for agricultural cooperatives, extension services, and agribusiness organizations. Cooperative models that share AI infrastructure and data analytics costs across multiple member farms can reduce per-farm investment burdens while maintaining access to precision farming benefits. Agricultural extension services should integrate digital advisory components into their traditional portfolios, training extension officers to support farmers in AI system selection, implementation, and troubleshooting. Agribusiness firms supplying inputs or purchasing outputs should consider offering AI decision-support tools as value-added services to strengthen farmer relationships and improve supply chain predictability.

Policy implications. Policymakers aiming to accelerate AI adoption in transitional agricultural systems should consider four priority actions. First, subsidize AI technology trials on demonstration farms to reduce perceived risk and generate locally relevant evidence. Second, invest in rural broadband infrastructure, identified as the primary adoption barrier in Serbia and similar contexts. Third, integrate digital competencies into agricultural extension services and vocational training programs. Fourth, create innovation vouchers or matching grants that enable smallholder access to AI advisory platforms, ensuring that digital transformation benefits are distributed equitably across farm size classes rather than concentrating among large enterprises.

Summary of Key Findings

This study demonstrates that AI-driven decision-support tools significantly enhance farm performance by increasing productivity, optimizing resources, and reducing operational costs. The findings confirm that digital transformation is not merely a technological shift but an economically viable pathway toward sustainable agricultural development. Empirical evidence shows that AI adoption leads to higher yields and superior input efficiency compared to conventional systems, enabling better responses to environmental and market volatility. Consequently, economic gains are directly coupled with reduced environmental pressure, specifically through optimized water and fertilizer use. These results provide robust quantitative evidence linking digital innovation with both microeconomic efficiency and macro-level sustainability.

Concluding Remarks

To maximize the benefits of AI in agriculture, coordinated action among stakeholders is essential. Policymakers must prioritize investment in rural digital infrastructure to overcome current barriers to adoption. Financial instruments, such as targeted subsidies and innovation grants, should be designed to ensure inclusive modernization for small and medium-sized farms. Furthermore, enhancing farmers' digital competencies through capacity-building initiatives is essential for long-term competitiveness. While this study is limited by its sample size and timeframe, it highlights the need for future longitudinal research across diverse regions. Ultimately, the successful integration of AI in agriculture requires coordinated action among researchers, policymakers, technology providers, and farming communities to foster resilient food systems and sustainable rural economies.

Conflict of interests

The authors declare no conflict of interest.

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