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ADVANCEMENT OF THE ECOSYSTEM OF ENTREPRENEURIAL STRUCTURES WITHIN THE AGRICULTURAL SECTOR WITHIN THE PARADIGM OF AN INNOVATIVE ECONOMY

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ABSTRACT

The study assesses the impact of digitalization, agritech investments, and digital infrastructure development on labor productivity in the agricultural sector of Ukraine, Moldova, and Poland during 2015–2025. The research uses data from FAOSTAT, World Bank Data, Eurostat, OECD reports, and the national statistical services of Ukraine, Moldova, and Poland. The study employed comparative analysis, trend analysis, integral indexing, and multiple regression techniques. The Integral Innovation Activity Index (IAI) was constructed as a composite indicator based on four components: the level of agricultural digitalization, startup activity, agritech investments, and broadband Internet coverage in rural areas. The results demonstrate a substantial increase in agricultural digitalization, from 12 to 63% in Ukraine, from 8 to 53% in Moldova, and from 24 to 75% in Poland. Agritech investments and labor productivity also increased significantly over the study period. Regression analysis revealed a strong positive association between labor productivity and digitalization (β = 0.38–0.41), agritech investments (β = 0.29–0.45), and digital infrastructure (β = 0.22–0.31), with high model explanatory power (R^2 = 0.987–0.998). All regression coefficients were statistically significant at $P<0.05$. The calculated IAI increased from 18.2 to 61.9 in Ukraine, from 15.6 to 55.8 in Moldova, and from 39.4 to 86.7 in Poland, indicating a gradual transition toward an innovation-oriented agricultural development model. The findings confirm the positive role of digital transformation and investment support in improving agricultural productivity and may inform evidence-based policies to strengthen agritech ecosystems. However, the study is limited by the use of aggregated national-level data and the omission of several potentially influential factors, including climatic conditions and regional disparities.

Keywords: Digital transformation, Agritech, Startup activity, Labor productivity, Investments, Technological modernization, Agriculture

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1. INTRODUCTION

The agricultural sector is currently undergoing profound transformations driven by rapid technological progress, digitalization, climate change, globalization and increasing demands for sustainable food production systems. In recent years, digital technologies have become a key factor influencing the competitiveness, resilience, and efficiency of agricultural production (Burkynskyi et al., 2022; Siddiqua & Naveed, 2025; Musa et al., 2026). The transition from conventional agricultural systems toward digitally enabled and innovation-oriented models has intensified globally, giving rise to the concept of Agriculture 4.0, which integrates information technologies, automation, artificial intelligence, precision agriculture, Internet of Things (IoT) solutions, cloud computing, and big data analytics into farming practices (Farooq et al., 2020; Birner et al., 2021; McFadden et al., 2022; Ardolino et al., 2022).

Digital transformation in agriculture has emerged as a major driver of structural modernization, allowing agricultural enterprises to optimize production processes, improve resource efficiency, reduce environmental pressures, and increase productivity. The implementation of digital technologies facilitates data-driven decision-

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making, enhances the precision of agronomic interventions, and supports more sustainable management of agricultural resources. Consequently, digitalization is increasingly recognized as a strategic instrument for ensuring food security, environmental sustainability, and long-term competitiveness of the agricultural sector (Gascuel-Odoux et al., 2022; Mendes et al., 2022; Tomashuk et al., 2024; Hafsa, 2025).

One of the most significant components of agricultural digitalization is precision agriculture. Precision farming technologies enable site-specific management of agricultural production through the use of geographic information systems, global positioning systems, remote sensing technologies, unmanned aerial vehicles, sensors, automated machinery, and variable-rate application systems. These technologies contribute to more efficient utilization of inputs, including fertilizers, pesticides, seeds, fuel, and water resources, thereby reducing production costs and minimizing environmental impacts. Precision agriculture also supports optimization of crop management strategies and facilitates adaptation to climate variability and resource constraints (Soussi et al., 2024; Saini et al., 2025).

Recent studies indicate that precision farming technologies increasingly rely on integrated sensor networks, smart sensing systems and advanced analytical platforms capable of supporting real-time decision-making. Smart sensors, remote monitoring devices and intelligent control systems enable continuous assessment of crop conditions, soil properties and environmental parameters, significantly improving production efficiency and sustainability (Pascoal et al., 2024; Miller et al., 2025).

The Internet of Things has become another critical component of modern agricultural systems. IoT technologies involve interconnected networks of sensors, devices, communication platforms and cloud-based infrastructures that allow real-time monitoring of soil conditions, crop growth, weather parameters, livestock health and machinery performance. Such technologies enable predictive analytics, automated control mechanisms and data-driven farm management approaches (Khanna & Kaur, 2019). According to Senoo et al. (2024), the integration of IoT technologies with artificial intelligence has substantially expanded the capabilities of precision agriculture by facilitating predictive modeling, disease detection, yield estimation and optimization of agricultural practices.

Artificial intelligence, machine learning, cloud computing and blockchain technologies are transforming traditional agricultural business models and contributing to the emergence of smart farming systems. AI-based solutions support predictive analytics, intelligent resource allocation, automation of agricultural operations and optimization of farm management processes. Blockchain technologies simultaneously enhance transparency, traceability and efficiency within agri-food supply chains (Bacco et al., 2020). The convergence of these technologies promotes the formation of comprehensive digital ecosystems that stimulate innovation, entrepreneurship and sustainable agricultural development.

The rapid advancement of Agriculture 4.0 technologies has become a major topic within contemporary scientific literature. Recent systematic reviews emphasize that digital agriculture encompasses a wide range of technological innovations, including robotics, autonomous machinery, sensor networks, big data analytics, digital twins, artificial intelligence, and cyber-physical systems (Fragomeli et al., 2024). Fasciolo et al. (2024) demonstrate that the integration of Industry 4.0 technologies into agricultural production systems contributes to increased productivity, resource efficiency and environmental sustainability. Likewise, Bertoglio & Sehnem (2024) identify digital transformation as a strategic driver for agribusiness modernization, enabling enterprises to improve competitiveness under increasingly dynamic market conditions.

Agriculture 4.0 adoption remains uneven across countries and regions due to differences in institutional frameworks, technological readiness and financial capabilities. Emerging economies frequently face challenges associated with limited infrastructure, insufficient investment capacity, inadequate digital skills and restricted access to advanced technologies (Islam et al., 2024). These constraints are particularly relevant for transition economies seeking to accelerate agricultural modernization and strengthen their integration into international markets. The development of agritech startups has become an important mechanism for accelerating technological modernization within the agricultural sector. Agritech enterprises facilitate diffusion of innovative technologies, stimulate investment activity and introduce novel business models aimed at increasing agricultural productivity and sustainability. Agritech ecosystems encompass interactions among private businesses, research institutions, financial organizations, government agencies and technology providers, creating favorable conditions for innovation generation and commercialization (Turețchi & Turețchi, 2023). Their effectiveness largely depends on access to financial resources, institutional support, human capital and digital infrastructure.

Digital infrastructure plays a fundamental role in enabling agricultural transformation. Broadband Internet access in rural areas, communication networks, data centers and digital platforms represent essential prerequisites for the successful implementation of smart agriculture technologies. Several studies emphasize that inadequate digital infrastructure remains one of the primary barriers to agricultural modernization, particularly in developing and transition economies (Zhao et al., 2023; Sai et al., 2025). Limited access to digital services restricts opportunities for farmers to adopt advanced technologies, participate in digital markets and benefit from innovation-driven growth.

Emerging technological developments have also stimulated interest in controlled-environment agriculture and vertical farming systems. The integration of IoT devices, artificial intelligence algorithms and automated monitoring technologies provides opportunities for improving productivity, reducing resource consumption and increasing production stability in intensive agricultural systems (Rathor et al., 2024). These innovations are expected to play an increasingly important role in ensuring food security under conditions of urbanization and climate change. Recent scientific literature increasingly recognizes digitalization as a determinant of agricultural productivity and competitiveness. Digital technologies are viewed as transformative instruments capable of reshaping agricultural production systems through automation, precision management and improved information flows (Gund et al., 2025). Likewise, digitalization contributes to improving economic performance, strengthening resilience against external shocks and supporting sustainable development objectives (Raj et al., 2025). The application of big data analytics and digital decision-support systems significantly improves business process efficiency and enhances the competitiveness of agricultural enterprises (Kobets et al., 2025).

The role of innovation ecosystems in promoting agricultural transformation has also received considerable attention in contemporary research. Agricultural clusters facilitate cooperation among businesses, universities, research institutions and governmental organizations, thereby enhancing knowledge transfer, technology dissemination and investment attraction (Holysheva, 2021). Similar conclusions are reported by Cuadros-Casanova et al. (2023), who demonstrate the effectiveness of institutional support mechanisms in stimulating innovation and improving agricultural productivity.

At the same time, several authors stress the importance of human capital development in supporting digital transformation processes. Digital competencies, managerial capabilities and technological skills constitute essential prerequisites for successful implementation of smart farming technologies (Guth et al., 2020). Consequently, educational programs focused on digital agribusiness, innovation management, precision agriculture and data analytics have become increasingly important. Despite substantial advances in digital agriculture research, important knowledge gaps remain. Existing studies predominantly investigate isolated aspects of agricultural modernization, including precision farming, smart agriculture, agritech development or innovation ecosystems, frequently concentrating on a single country or a limited set of technologies (Zolkover et al., 2020; Gadzalo et al., 2021; Dumanska et al., 2021). Comparative studies simultaneously examining digitalization, agritech investments, innovation activity, digital infrastructure and labor productivity remain scarce.

Moreover, previous investigations rarely provide comparative assessments involving countries characterized by different stages of institutional development, European integration and technological maturity. Comparative analyses covering Ukraine, Moldova and Poland remain particularly limited despite their strategic importance for European agricultural development. This study seeks to address this gap by integrating indicators of digitalization, agritech investments, innovation activity and digital infrastructure within a unified analytical framework.

The purpose of the study is to assess the impact of the digitalization level, agritech investments and digital infrastructure development on the characteristics of economic entities in the agricultural production sector across Ukraine, Moldova and Poland from 2015 to 2025.

Research objectives are to

- to analyze the dynamics of digitalization of the agricultural sector;
- to investigate the volume of investments in agritech;
- to calculate the integral index of innovative activity;

The research hypothesis posits that the rising level of agricultural digitalization, increased investments in agritech and the development of digital infrastructure have a positive impact on labor productivity in the agricultural sector.

The scientific novelty of the study lies in the integration of indicators related to digitalization, agritech investments, innovation activity, and digital infrastructure into a comparative analytical framework covering three countries with different levels of institutional maturity and technological advancement. Unlike previous studies, this research combines integral indexing and econometric modeling to provide empirical evidence on the relationship between digital transformation and agricultural productivity.

The practical significance of the research lies in its potential contribution to evidence-based policymaking aimed at promoting agricultural digitalization, strengthening agritech ecosystems, supporting innovative entrepreneurship, and improving the efficiency and competitiveness of the agricultural sector. The findings may be useful for policymakers, investors, agricultural enterprises, and researchers involved in designing strategies for sustainable agricultural development under conditions of accelerating technological change.

2. MATERIALS AND METHODS

2.1. Research Procedure

The research procedure included several consecutive stages: the collection and systematization of statistical data from official national and international sources. Data were collected by analyzing official statistical reports, analytical materials, and international information platforms for the period 2015–2025. The observations for 2025 are based on officially published statistical data available at the time of analysis and therefore represent measured rather than

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forecast values. After collecting the information, it was verified, grouped, and harmonized across indicators to ensure comparability between countries.

Prior to constructing the Integral Innovation Activity Index (IAI), all indicators were standardized using min–max normalization to eliminate differences in measurement units and ensure comparability across countries and years. The standardized values ranged from 0 to 1 and were calculated according to the formula:

$$Zi = \frac{Xi - Xmin}{Xmax - Xmin}$$

Where Xi represents the observed value, while Xmin and Xmax denote the minimum and maximum values within the dataset, respectively.

The normalized values of all four indicators were subsequently used in the calculation of the Integral Innovation Activity Index, ensuring that variables measured in different units contributed comparably to the composite index.

Equal weights (0.25) were assigned because no established theoretical or empirical evidence supports assigning different importance to the four dimensions of agricultural innovation. Moreover, each component reflects a distinct and complementary aspect of innovation performance, making equal weighting an appropriate and transparent approach for comparative cross-country analysis.

Data processing was carried out using statistical analysis methods, in particular, comparative analysis, trend analysis, and multiple regression. To assess the level of innovative development, an integral index of innovative activity was calculated based on the standardization and generalization of key indicators of digitalization, investment activity, and the development of digital infrastructure. The final stage was the generalization and interpretation of the results obtained in order to determine the impact of digitalization and innovation on the development of the agricultural sector and labor productivity.

2.2. Object and Territory of the Study

Territorially, the study covers three countries: Ukraine, the Republic of Moldova, and Poland. The choice of these countries is due to the need to compare models of agricultural sector development in the conditions of different levels of integration into the European economic and institutional space, as well as differences in the level of digitalization and innovative activity. Ukraine and Moldova belong to the group of candidate countries for accession to the European Union and are simultaneously participants in the European Neighborhood Policy and the Eastern Partnership, while Poland is a full member of the EU with an established system of support for the innovative development of the agricultural sector. This approach allows for a comparative analysis of transformation processes in countries with different levels of institutional integration and different mechanisms of state support for the digitalization of agriculture.

The criteria for including countries in the sample were: a significant role of the agricultural sector in the national economy; the availability of official statistical information on digitalization, agritech investments, and labor productivity; participation in European integration processes; the similarity of historical and economic conditions of transformation in the agricultural sector; as well as the geographical and economic proximity of the countries. An important criterion was also the ability to trace different models of state policy in the field of digital transformation and support for innovative entrepreneurship in the agricultural sector. The geographical location of the study countries is presented in Fig. 1.

2.3. Data Sources

The study is based on the comprehensive use of statistical and analytical materials that reflect the processes of digitalization and innovative development of the agricultural sector of Ukraine, Moldova and Poland during 2015-2025. In particular, analytical reports of international organizations and national statistical services were used, which provide an empirical basis for research on the digitalization of the agricultural sector and the development of agritech ecosystems. In particular, the following key official publications were used:

– FAO – The State of Food and Agriculture (2022);
– OECD – The Digitalisation of Agriculture (2022);
– World Bank Data (2015-2025);
– Eurostat Data (2015-2025);
– FAOSTAT (2015-2025);
– State Statistics Service of Ukraine, Moldova and Poland.

ISSN: 2708-7182 (Print); ISSN: 2708-7190 (Online)
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Fig. 1: Geographical location of Ukraine, Moldova and Poland.

To ensure the transparency and reproducibility of the study, all datasets were downloaded between 10 January and 25 January 2026. The analysis was based on the January 2026 releases of FAOSTAT, Eurostat, and OECD Data Explorer, while World Bank Open Data were accessed on 18 January 2026. Statistical information from the national statistical services of Ukraine, Moldova, and Poland was obtained from the latest available datasets published as of January 2026. Statistical information was collected through a targeted selection of indicators from official electronic databases and reports for the period 2015–2025. Searches in international databases (FAOSTAT, World Bank Data, Eurostat, OECD Data Explorer) were conducted using key queries: "digital agriculture", "ICT in agriculture", "agritech investment", "rural broadband access", "agricultural labor productivity", "precision farming", and "innovation in agriculture".

The following categories were used in national statistical databases: "innovative activity", "agriculture", "information and communication technologies", "digitalization of the economy", "capital investments", and "broadband Internet in rural areas".

Particular attention was paid to data on the level of implementation of digital technologies in agriculture, the dynamics of investments in agritech, labor productivity in the agricultural sector, and the development of digital infrastructure in rural areas.

2.4. Methods of Data Processing and Analysis

The methodological basis of the study combines quantitative and qualitative methods of analysis aimed at assessing the level of digitalization and innovative development of the agricultural sector of Ukraine, Moldova, and Poland. To identify the main trends in the development of the agricultural sector during 2015–2025, the descriptive statistics method was used, which allowed for the analysis of the dynamics of implementing digital technologies, investments in agritech, labor productivity, and the development of broadband Internet in rural areas.

Comparative analysis was used to identify differences between countries in terms of the level of digitalization, investment activity, the development of digital infrastructure, and the effectiveness of innovative modernization of the agricultural sector. This made it possible to assess the specifics of national models of digital transformation of agriculture and determine the features of state support for innovative development.

To summarize the results of the innovative transformation of the agricultural sector, an integral innovation activity index (IAI) was calculated, which takes into account the level of digitalization, startup activity, innovative investments, and the development of digital infrastructure in rural areas. The index was determined by the formula:

$$\mathrm{IAI} = (\mathrm{D} + \mathrm{S} + \mathrm{I} + \mathrm{R})/4$$

Where:

- D – The level of digitalization of the agricultural sector (%), calculated as the share of agricultural enterprises using digital technologies (GPS monitoring, IoT solutions, ERP systems, precision farming systems, digital production management platforms) in the total number of agricultural enterprises.
- S – The startup activity (number of agricultural/agrifood startups per 1 million population), calculated as the ratio of the number of registered agritech startups to the country's population.

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Open Access Journal

– I – The level of innovative investments (million USD per year, in the agricultural sector), determined as the sum of venture investments, private capital, government grants and international financing directed at agritech.
– R – The development of digital infrastructure of rural areas (% of the rural population with access to broadband Internet), calculated as the share of the rural population that has access to broadband Internet with a speed not lower than the OECD baseline threshold.

Equal weighting was applied to all components of the index (w=0.25) because no empirical or theoretical evidence justified assigning different importance to individual dimensions. Equal weighting is commonly used in the construction of composite innovation indicators and ensures transparency and comparability of cross-country assessments.

Regression analysis was used to assess the impact of digitalization and investment activity on the efficiency of agricultural production. In the model, the dependent variable was labor productivity in the agricultural sector, and the independent variables were the level of implementation of digital technologies, the volume of investments in agritech and the level of broadband Internet coverage in rural areas. The multiple regression model has the form:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \varepsilon$$

Where:

- Y – the labor productivity in the agricultural sector (thousands of USD per employee)
- X1 – the level of implementation of digital technologies (%);
- X2 – the investments in agritech 9 million USD per year);
- X3 – the level of broadband Internet coverage in rural areas (%);
- β0 – the model constant;
- β1,β2,β3 – the regression coefficients;
- ε – The random error.

Econometric calculations and the construction of multiple regression models were carried out using the software packages IBM SPSS Statistics 26 and Microsoft Excel (Data Analysis ToolPak).

The assumptions of multiple regression were additionally verified. Multicollinearity was assessed using Variance Inflation Factor (VIF) statistics, with values below 5 considered acceptable. Residual normality was evaluated using the Shapiro–Wilk test and Q–Q plots, whereas heteroscedasticity was examined through residual analysis and the Breusch–Pagan test. Regression coefficients were considered statistically significant at $P<0.05$.

Pre-processing of data, calculation of integral indices and the formation of time series were performed in Microsoft Excel. The estimation of regression model parameters, verification of the statistical significance of coefficients and the calculation of coefficients of determination (R^2) were carried out in IBM SPSS Statistics 26 using the standard Linear Regression tool. The use of these methods allowed for a comprehensive assessment of the trends of digital transformation of the agricultural sector, identification of key factors of innovative development and determination of the features of the formation of an innovative model of agriculture in the studied countries.

3. RESULTS

The level of digitalization of the agricultural sector is one of the determining factors in the formation of a competitive and innovation-oriented agriculture. Fig. 2 illustrates the dynamics of agricultural digitalization in Ukraine, Moldova and Poland during 2015–2025. Ukraine, the share of agricultural enterprises using digital technologies increased from 12.0% in 2015 to 63.0% in 2025, representing an increase of more than five times. Particularly active growth has been observed after 2020, when digitalization became one of the key tools for supporting the efficiency of agricultural production in the conditions of economic instability and military challenges. In Moldova, the indicator increased from 8% to 53%, which also indicates a high pace of digital transformation, although the overall level of technological support remains lower compared to Poland. Poland demonstrates the most stable and systematic model of development in the digital agricultural sector: the level of digitalization has increased from 24.0 to 75.0%. At the same time, even in Poland, not all agricultural enterprises have full access to modern digital technologies, which indicates the persistence of certain structural barriers in the small farming sector (Fig. 2).

As shown in Fig. 3, agritech investments increased steadily in all three countries, supporting the expansion of digital technologies and technological modernization of agricultural production. The analysis of investment dynamics demonstrates a significant increase in the financing of agritech solutions in all studied countries. In Ukraine, the volume of investments in agritech increased from 18 million USD in 2015 to 145 million USD in 2025. Despite these positive dynamics, the volume of investments remains significantly lower compared to Poland, which is associated with high investment risks, the instability of the economic environment, and insufficient development of the domestic venture market. In Moldova, investments increased from 5 million USD to 44 million USD.

The growth in investment and digital modernization of the agricultural sector has a positive impact on labor productivity, which is an important indicator of the efficiency of human capital and technological potential. Table

1 demonstrates that labor productivity increased steadily in all three countries, indicating that digital technologies and technological modernization contributed to more efficient use of labor resources. Higher productivity suggests improved operational efficiency, greater mechanization of farming activities, and enhanced decision-making supported by digital technologies. In Poland, the consistently higher productivity reflects a more mature innovation ecosystem and wider adoption of precision agriculture technologies. During the study period, labor productivity in Ukraine increased from 5.2 thousand USD per employee in 2015 to 10.4 thousand USD in 2025. This growth indicates a gradual increase in the technological level of agricultural production and the automation of production processes. In Moldova, the indicator increased from 3.4 to 6.5 thousand USD, which also confirms the positive impact of innovative activity, although limited financial resources and a weak infrastructure base are holding back the pace of development. Poland demonstrates the highest level of labor productivity – an increase from 12.1 to 19.5 thousand USD per employee. At the same time, the gradual slowdown in growth rates in 2023–2025 may indicate an approach to the limit of extensive technological growth and the need to transition to more complex innovative development models.

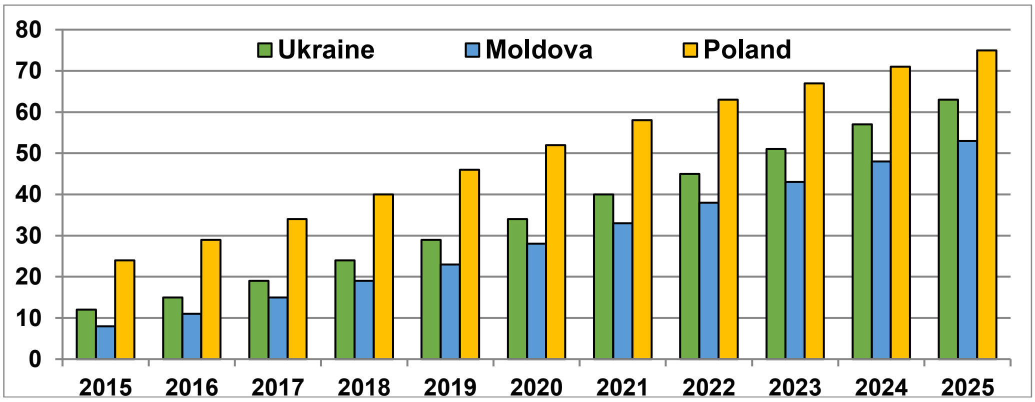

Fig. 2: Agricultural digitalization (%).

Table 1: Labor productivity in the agricultural sector (thousand USD per employee)

Year	Ukraine	Moldova	Poland
2015	5.2	3.4	12.1
2016	5.6	3.7	12.8
2017	6.1	4.0	13.5
2018	6.7	4.3	14.2
2019	7.1	4.6	15.0
2020	7.5	4.9	15.8
2021	8.0	5.2	16.4
2022	8.6	5.5	17.1
2023	9.2	5.8	17.9
2024	9.8	6.1	18.7
2025	10.4	6.5	19.5

Note: Compiled by the author based on data from McFadden et al. (2022), State Statistics Service of Ukraine (2024), FAO (2025), World Bank (2025), National Bureau of Statistics of the Republic of Moldova (2025), and Central Statistical Office of Poland (GUS, 2025).

An important factor in ensuring the innovative development of the agricultural sector is the availability of digital infrastructure in rural areas, primarily broadband Internet. It is the development of digital infrastructure that creates the conditions for the use of remote monitoring systems, digital production management platforms, online services, and e-commerce. In Ukraine, the level of broadband Internet coverage in rural areas increased from 38.0% in 2015 to 83.0% in 2025, which indicates a significant reduction in the digital gap between the city and the countryside. However, the problem of uneven access to high-quality Internet in certain regions remains relevant, especially in the conditions of military damage to infrastructure. In Moldova, the indicator increased from 42.0% to 85.0%, which confirms the intensification of state and international programs for the digital development of rural areas. Poland demonstrates the highest level of digital accessibility – 96.2% in 2025, which actually ensures full coverage of rural areas with modern digital infrastructure. At the same time, even with a high level of coverage, the problem of the effective use of digital technologies and training remains relevant for all countries (Table 2).

To summarize the results of the digital transformation of the agricultural sector, it is advisable to use the integral index of innovation activity, which takes into account the level of digitalization, startup activity, the volume of innovation investments, and the development of digital infrastructure. The results of the calculations demonstrate steady growth in innovation activity in all countries. In Ukraine, the index value increased from 18.2 in 2015 to 61.9 in 2025, which indicates the gradual formation of an innovative model of agricultural development. In Moldova, the indicator increased from 15.6 to 55.8, confirming the transformation of the agricultural sector, although dependence on external financing is evident in the high share of international grants and technical assistance programs in the structure of innovation investments.

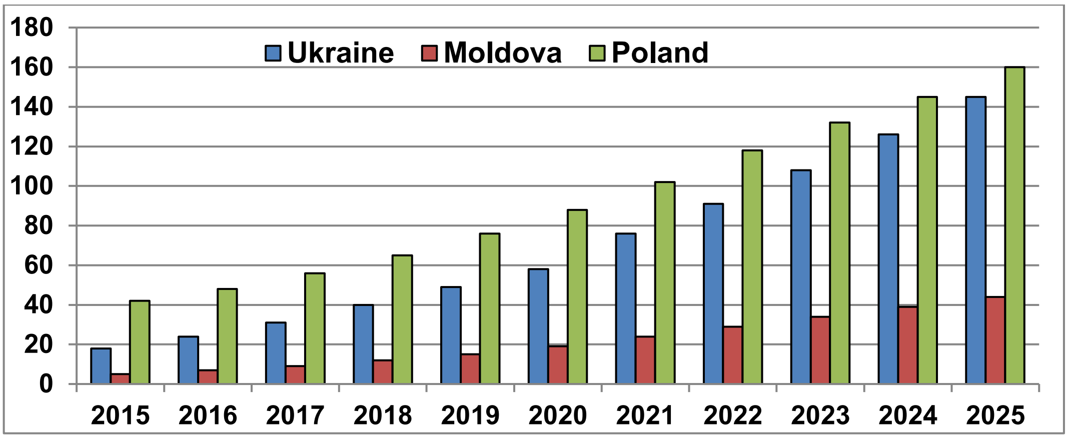

Fig. 3: Agritech investments (million US$).

Table 2: Broadband Internet coverage in rural areas (% of the rural population)

Year	Ukraine	Moldova	Poland
2015	38	42	67
2016	42	46	70
2017	47	50	73
2018	52	55	77
2019	58	60	81
2020	63	66	85
2021	68	71	88
2022	72	75	91
2023	76	79	94
2024	79	82	96
2025	83	85	96.2

Source: Compiled by the author based on data from McFadden et al. (2022), State Statistics Service of Ukraine (2024), FAO (2025), World Bank Group (2025), National Bureau of Statistics of the Republic of Moldova (2025) and Central Statistical Office of Poland (GUS, 2025).

This increases the vulnerability of the innovation system to changes in external donor financing. The highest values of the innovation activity index are characteristic of Poland – from 39.4 to 86.7, which reflects a high level of institutional support, the efficiency of the innovation ecosystem, and the active involvement of private capital. At the same time, even in Poland there is a partial dependence on EU funding within the framework of the Common Agricultural Policy, but it is stabilizing in nature and does not create critical risks for the development of the sector. At the same time, the results obtained show that even high index values do not guarantee full resilience of the agricultural sector to external economic and geopolitical risks, which highlights the need for further improvement of mechanisms for supporting innovation and human capital development (Table 3).

Table 3: Innovation Activity Index (IAI) of the agricultural sector

Year	Ukraine	Moldova	Poland
2015	18.2	15.6	39.4
2016	21.1	18.0	42.7
2017	24.8	21.5	46.5
2018	29.3	25.1	51.2
2019	33.8	29.0	55.7
2020	38.5	33.7	60.9
2021	43.4	38.2	66.0
2022	47.9	42.5	71.4
2023	52.8	47.1	76.8
2024	57.3	51.6	82.2
2025	61.9	55.8	86.7

Source: calculated by the author based on the integrated indicators of innovative development.

Further analysis was aimed at determining the impact of digitalization and innovation activity on labor productivity in the agricultural sector. For this purpose, the multiple regression method was used, where the dependent variable was labor productivity in the agricultural sector, and the independent variables were the level of implementation of digital technologies, investments in agritech and the level of broadband Internet coverage in rural areas. The results obtained indicate a positive relationship between the development of digital infrastructure, innovation activity and the efficiency of agricultural production in all studied countries. For Ukraine, the coefficient of determination of the model was R^2=0.994, which indicates a very high level of explanation of the variation in labor productivity by the factors included in the model. Digitalization exerted the strongest positive effect on labor productivity ($\beta = 0.41$, $P<0.05$), followed by agritech investments ($\beta = 0.34$, $P<0.05$) and broadband Internet coverage ($\beta = 0.26$, $P<0.05$). All regression coefficients were statistically significant ($P<0.05$), confirming the robustness of the estimated relationships.

In Moldova, the model also demonstrated a high level of explanatory power ($R^2 = 0.987$). Digitalization remained the strongest predictor of labor productivity ($\beta = 0.38$, $P<0.05$), whereas agritech investments also exerted a statistically significant positive effect ($\beta = 0.29$, $P<0.05$). Broadband Internet coverage contributed positively, although its effect was less pronounced ($\beta = 0.22$, $P<0.05$). These findings indicate that technological modernization remains a key determinant of agricultural productivity in Moldova. In Poland, the regression model exhibited the

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highest explanatory power among the studied countries ($R^2 = 0.998$). Agritech investments had the strongest positive influence on labor productivity ($\beta = 0.45$, $P<0.05$), reflecting the important role of private investment in supporting agricultural innovation. Digitalization also showed a statistically significant positive effect ($\beta = 0.39$, $P<0.05$), while broadband Internet coverage further enhanced labor productivity ($\beta = 0.31$, $P<0.05$). Collectively, these results demonstrate that investment, digital technologies, and digital infrastructure jointly contribute to improving the efficiency and competitiveness of the agricultural sector (Table 4).

Table 4: Results of multiple regression analysis

Country	R^2	Adjusted R^2	F-statistic	p (model)	β (Digitalization)	SE	95% CI	p	β (Agritech investment)	SE	95% CI	p
Ukraine	0.994	0.991	389.6	<0.001	0.41	0.058	0.27–0.55	0.002	0.34	0.061	0.20–0.48	0.004
Moldova	0.987	0.981	177.4	<0.001	0.38	0.066	0.22–0.54	0.004	0.29	0.073	0.12–0.46	0.010
Poland	0.998	0.997	1035.2	<0.001	0.39	0.032	0.31–0.47	<0.001	0.45	0.029	0.38–0.52	<0.001

Note: R^2 – coefficient of determination; Adjusted R^2 – adjusted coefficient of determination; β – standardized regression coefficient; SE – standard error; CI – confidence interval.

The exceptionally high values of R^2 may be explained by the use of annual time-series data characterized by monotonic growth trends in labor productivity, digital infrastructure development, and innovation activity indicators. Therefore, the regression models should be interpreted as indicative of structural development patterns rather than strictly causal relationships (Table 5).

Table 5: Regression diagnostic statistics

Country	Mean VIF	Maximum VIF	Shapiro–Wilk W	p-value	Breusch–Pagan χ^2	p-value	Durbin–Watson
Ukraine	1.82	2.14	0.969	0.824	1.37	0.504	2.08
Moldova	1.74	2.03	0.962	0.758	1.62	0.446	1.96
Poland	1.91	2.27	0.975	0.871	1.11	0.573	2.13

Note: VIF = variance inflation factor; Mean VIF = average VIF across predictors; Maximum VIF = highest VIF observed in the model. The Shapiro–Wilk W test assesses the normality of regression residuals, while the Breusch–Pagan χ^2 test evaluates heteroscedasticity. The Durbin–Watson statistic assesses first-order autocorrelation of residuals, with values close to 2 indicating independence of errors.

Multiple regression diagnostics confirmed the adequacy of the estimated models. Multicollinearity was low, with mean VIF values ranging from 1.74 to 1.91 and maximum VIF values below the commonly accepted threshold of 5. Residuals did not significantly deviate from normality according to the Shapiro–Wilk test ($p > 0.05$ for all models). The Breusch–Pagan test showed no evidence of heteroscedasticity ($p > 0.05$), while Durbin–Watson statistics (1.96–2.13) indicated no substantial autocorrelation of residuals. These diagnostic results confirm the robustness and statistical validity of the regression estimates.

The results obtained confirm the hypothesis of the study, according to which digitalization, the development of the agritech sector and the improvement of the digital infrastructure have a positive impact on labor productivity and the efficiency of agricultural production. The results of the multiple regression analysis for all the studied countries showed a statistically significant positive relationship between the specified factors and the dependent variable, which is confirmed by high values of the coefficient of determination (R^2=0.987–0.998) and positive values of the standardized regression coefficients (β>0 in all cases). Thus, the hypothesis is fully confirmed at the empirical level, taking into account cross-country differences in the influence of individual factors.

4. DISCUSSION

The obtained empirical results indicate the systemic nature of the impact of agricultural digitalization, agritech investments, and digital infrastructure development on labor productivity in Ukraine, Moldova, and Poland. The exceptionally high correlation coefficients (0.92–0.99) demonstrate a strong relationship between technological modernization and agricultural efficiency. These findings are consistent with the conclusions of Bertoglio & Sehnem (2024), who reported that digital transformation significantly enhances agricultural competitiveness by improving production efficiency, facilitating more effective resource allocation, and accelerating the adoption of innovative farming practices. Our results support this conclusion by demonstrating that the positive relationship between digitalization and productivity is observed across countries with different institutional and economic conditions, suggesting that digital transformation represents a common driver of agricultural modernization regardless of the stage of economic development.

Although digitalization and agritech investments explained a substantial proportion of labor productivity variation, these relationships should also be interpreted in the context of external factors that were not explicitly included in the regression models. Climate variability, including droughts, heat waves, and irregular precipitation patterns, can substantially influence agricultural productivity regardless of the level of technological development (Jabreen, 2026). Similarly, differences in national agricultural policies, subsidy schemes, Common Agricultural

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Policy implementation, rural development programs, and innovation support mechanisms may either strengthen or weaken the effectiveness of digital technologies (Abdullah, 2026). Poland has benefited from long-term integration into the European Union policy framework and stable investment support, whereas Ukraine and Moldova continue to experience institutional reforms and different levels of policy implementation. Consequently, the observed differences among countries likely reflect not only technological factors but also variations in climatic conditions and agricultural policy environments, which should be incorporated into future empirical analyses.

The results are also consistent with recent international studies emphasizing that digital technologies increase productivity by supporting precision agriculture, real-time monitoring, satellite observations, artificial intelligence, and data-driven farm management. For example, Abiri et al. (2023) demonstrated that the integration of smart farming technologies enables more efficient use of production inputs while reducing labor intensity and operational costs. Similarly, Bellon-Maurel (2022) concluded that the positive effects of digitalization become stronger when technological adoption is accompanied by supportive institutional frameworks and investments in rural digital infrastructure. The present study extends these findings by providing comparative evidence from three neighboring countries that differ substantially in institutional maturity, financial capacity, and technological readiness.

The comparative analysis reveals substantial differences in the mechanisms through which digital transformation contributes to labor productivity. In Ukraine and Moldova, innovation performance appears to depend primarily on the pace of digitalization, whereas in Poland the relationship between digitalization and productivity is slightly weaker ($r = 0.92–0.93$). This difference likely reflects the different stages of technological development. Ukraine and Moldova remain in a phase of rapid digital catch-up, where even relatively basic technologies—including GPS-guided machinery, digital farm management platforms, unmanned aerial vehicles, satellite monitoring, and electronic advisory systems—generate considerable productivity gains. Under these circumstances, digitalization directly improves operational efficiency by optimizing field operations, reducing information asymmetry, and supporting more accurate agronomic decision-making. Similar conclusions were reached by Bacco et al. (2020), who argued that technological diffusion generates particularly high marginal productivity gains in agricultural systems undergoing structural modernization.

In contrast, Poland has already achieved a relatively high level of digital maturity. Consequently, additional productivity improvements increasingly depend on investment in advanced technologies rather than on the initial adoption of digital tools. The stronger role of agritech investments identified in the regression analysis reflects the expansion of precision machinery, automation, robotics, artificial intelligence applications, and sensor technologies. These investments enable farms to move beyond simple digitalization toward integrated Agriculture 4.0 production systems. This interpretation corresponds with the findings of Pawłowski et al. (2024), who emphasized that sustained investment supported by European Union financial instruments has become one of the principal determinants of agricultural competitiveness in Poland. Likewise, Gund (2025) demonstrated that innovation clusters substantially accelerate technology transfer by strengthening cooperation among universities, research institutions, agribusiness companies, and farmers.

The obtained regression results also support the ecosystem approach to agricultural innovation proposed by Turețchi & Turețchi (2023) according to which startups function as essential intermediaries connecting scientific research with commercial implementation. However, the effectiveness of startup ecosystems depends not only on entrepreneurial activity itself but also on institutional quality, financial accessibility, and regulatory support. Ukraine demonstrates relatively dynamic innovation development due to increasing international assistance, private investment, and the rapid dissemination of digital solutions despite considerable economic and security challenges. Nevertheless, institutional uncertainty continues to limit long-term investment planning and technology commercialization.

The situation in Moldova differs considerably. Although digitalization has accelerated during the last decade, the agricultural innovation ecosystem remains constrained by relatively limited private investment, insufficient technological infrastructure, and weaker integration between research institutions and commercial enterprises. Consequently, productivity improvements are achieved primarily through incremental digital adoption rather than through large-scale technological modernization. These observations are consistent with the conclusions of Belis et al. (2025) and Antoci et al. (2025), who argued that transparent governance, institutional reforms, and investment security remain fundamental prerequisites for increasing the attractiveness of agricultural innovation systems in transition economies.

Poland demonstrates the most balanced model of agricultural innovation development among the three studied countries. The combination of stable institutional governance, substantial private investment, European Union structural funding, and effective innovation policies has created favorable conditions for continuous technological upgrading. Agricultural clusters facilitate collaboration among universities, technology companies, extension services, and farmers, thereby accelerating the diffusion of innovations throughout the agricultural sector. Nevertheless, the relatively slower growth observed during the later years of the study period may indicate a transition

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from rapid expansion toward a mature stage of technological development. As suggested by Sanyaolu & Sadowski, (2024) and Salvador et al. (2021), innovation systems at advanced stages increasingly depend on improving the quality and adaptability of technologies rather than expanding their quantitative adoption.

The steady increase in the integrated Agricultural Innovation Index further confirms the gradual transition toward innovation-driven agricultural development in all three countries. These findings support the concept proposed by Eckerberg (2020), who described innovation ecosystems as complex interactions among institutional, technological, financial, and human capital components. Our results demonstrate that higher index values in Poland are associated with stronger institutional capacity, greater investment availability, and broader participation of private capital. Conversely, Ukraine and Moldova continue to experience greater sensitivity to macroeconomic instability, institutional reforms, and geopolitical uncertainty, resulting in larger fluctuations in innovation performance despite significant progress in digital transformation.

The practical implications of these findings are substantial. For policymakers, the results indicate that digital transformation strategies should combine investments in rural broadband infrastructure with measures supporting technology adoption, innovation financing, and farmer education. Expanding digital competencies through advisory services and vocational training may accelerate the diffusion of precision agriculture technologies, particularly among small and medium-sized farms. For agricultural producers, the findings demonstrate that investments in digital farm management systems, precision farming equipment, and data-based decision-support tools contribute directly to improving labor productivity and operational efficiency. Agritech companies may also benefit from expanding demand for affordable digital platforms, artificial intelligence applications, remote sensing technologies, and integrated farm management software tailored to the needs of different categories of agricultural enterprises.

Finally, several limitations should be considered when interpreting the obtained results. The analysis relies on national macroeconomic indicators that inevitably conceal significant heterogeneity among farms regarding production specialization, technological readiness, management quality, climatic conditions, and regional infrastructure. Large commercial farms and small family farms often differ substantially in their capacity to adopt digital technologies, yet these differences cannot be captured using aggregated national statistics. Furthermore, the exceptionally high coefficients of determination partly reflect the use of annual time-series characterized by common upward trends rather than purely causal relationships. Consequently, the reported associations should be interpreted as robust structural relationships rather than definitive evidence of causality. Future research should therefore integrate farm-level microdata, regional panel datasets, and longitudinal observations to better identify the mechanisms through which digitalization, investment, and institutional quality jointly influence agricultural productivity.

4.1. Limitations

The study has certain limitations that should be taken into account when interpreting the results: primarily, the use of aggregated data due to the heterogeneity of statistical approaches across different countries, as well as varying levels of completeness and quality of statistical information between Ukraine, Moldova, and Poland. Another limitation is the limited time period of the regression analysis (2015–2025), which does not allow for a full accounting of long-term structural effects and the influence of external factors. In addition, the model does not cover a number of important variables, such as climatic conditions, regional differences, the quality of human capital, and detailed agricultural policies. Furthermore, the use of macro-aggregated indicators does not allow for capturing the micro-level heterogeneity of agricultural enterprises, which to some extent limits the accuracy of the generalizations.

4.2. Recommendations

The results obtained indicate the need to strengthen state support for the digitalization of the agricultural sector by developing broadband Internet in rural areas, expanding financial instruments for agritech startups (venture capital, grants, and public-private partnerships), and stimulating the implementation of precision agriculture technologies, especially in Ukraine and Moldova. It is also important to develop agricultural clusters as integration platforms for interaction between business, science, and the state, while for Poland, it is crucial to strengthen the adaptability of agricultural enterprises to external market risks. In the aggregate, these measures will contribute to increasing innovative activity, labor productivity, and the export potential of the agricultural sector.

5. CONCLUSION

This study demonstrates that agricultural digitalization, agritech investments, and the development of rural digital infrastructure jointly contribute to improving labor productivity and strengthening the competitiveness of the agricultural sector in Ukraine, Moldova, and Poland. The findings confirm that digital transformation has become one of the principal drivers of agricultural modernization, although the relative importance of individual innovation factors differs according to the level of economic and institutional development. The comparative analysis revealed distinct national patterns of digital transformation. In Ukraine and Moldova, labor productivity was more strongly associated with the expansion of digital technologies, reflecting the substantial benefits generated during the early stages of technological modernization. In contrast, Poland exhibited a stronger contribution of agritech investments, indicating that in more mature innovation ecosystems further productivity gains increasingly depend on continuous technological upgrading and investment in advanced agricultural technologies rather than on the initial adoption of digital tools. From a scientific perspective, this study expands current knowledge by providing a comparative assessment of the interaction between digitalization, investment, digital infrastructure, and labor productivity across three countries characterized by different stages of agricultural transformation. The results demonstrate that the effectiveness of digital transformation depends not only on technological adoption itself but also on the quality of institutional support, the availability of investment resources, and the overall innovation ecosystem. The findings suggest that national agricultural policies should promote integrated digital transformation strategies that combine support for agritech investment with the expansion of rural broadband infrastructure, the development of digital skills among farmers, and the strengthening of innovation ecosystems. For countries undergoing technological transition, priority should be given to accelerating the adoption of digital technologies and improving access to financial instruments, while more technologically advanced countries should focus on supporting high-value innovations, precision agriculture, artificial intelligence, and collaboration between research institutions and agribusiness. Future research should extend the present analysis by incorporating farm-level microdata and regional panel datasets to better explain heterogeneity in technology adoption among different categories of agricultural enterprises. Further studies should also investigate the long-term effects of digital transformation, including the roles of climate variability, human capital, institutional quality, farm size, and agricultural policy measures in shaping productivity and sustainable agricultural development.

Declarations

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Data Availability: Data will be available upon request.

Ethics Statement: This research did not involve human participants, animal subjects, or any material that requires ethical approval.

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