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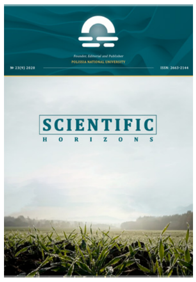

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The impact of digital platforms and artificial intelligence capabilities on product sales by small farms

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Abstract. The aim of the study was to assess the impact of digital platforms and artificial intelligence technologies on the sales efficiency of agricultural products by small farming households in Kazakhstan, compared with the experience of Central Asian countries and global practices. The study was conducted from March 2023 to February 2025 in 14 regions of the Republic of Kazakhstan using a comprehensive methodology, including a stratified random sample, structured interviews with

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managers of 324 small farming households (with up to 10 employees and an annual turnover not exceeding 30 million tenge), and 27 expert interviews with representatives of 8 digital platforms (AgroSmart.kz, Egistic, DigiField, QazFarm, AgroMap, Agroplatforma.kz, Agro.kz, Farm.kz). ANOVA, regression, and correlation analysis were performed, as well as machine learning methods (Random Forest, XGBoost) used for developing a predictive model. Statistical data analysis showed that the introduction of digital tools enabled an average sales increase of 27.3% with a reduction in intermediary costs of 18.6%. The highest efficiency was demonstrated by households using a combination of local trading platforms (AgroSmart.kz, Agro.kz) and specialised demand forecasting services. Regional analysis revealed significant differences in the level of digitalisation: in southern regions (Turkestan, Zhetysu), 64.2% of farmers regularly used at least two digital sales channels, whereas in the northern regions (Kostanay, North Kazakhstan), this figure was only 38.7%. The predictive model developed using machine learning algorithms showed a forecasting accuracy for seasonal demand fluctuations of 87.4% when tested on historical data from 2018-2023. The pilot implementation of the developed recommendations in the activities of 23 small farming households resulted in an average revenue increase of 31.5% and a 43.2% reduction in time spent searching for buyers. The study proved the economic feasibility of introducing digital tools into the practice of small farming households in Kazakhstan, even with a limited digitalisation budget

Keywords: small farming households; agro-industrial complex; digital platforms; sales efficiency; demand forecasting model; Kazakhstan; machine learning

INTRODUCTION

Digital platforms represented a key tool for transforming agri-food systems by expanding product sales channels, enabling direct interaction between producers and end consumers, and reducing intermediary costs. In Kazakhstan, small farming households accounted for 75% of all agricultural producers and provided 36.4% of the gross output of the agricultural sector, which formed 5.1% of the country's GDP (Organisation for Economic Co-operation and Development, 2023). At the same time, according to data from the Ministry of Agriculture of the Republic of Kazakhstan (n.d.), due to inefficient sales channels and lack of digitalisation, small farms lost up to 28% of potential profits annually, which amounted to around USD 1.2 billion on a national scale. The platform model aggregated information on demand, prices, and market trends, enabling prompt managerial decisions on product sales (Adamkulova *et al.*, 2025). As noted by A. Oliveira-Jr *et al.* (2020), the implementation of digital tools allowed farmers to shorten the chain of intermediaries and increase sales margins by 15-23% in developing countries. Studies by A. Glaros *et al.* (2023) indicated potential income growth for farmers through improved market access and optimisation of production processes. According to the Food and Agricultural Organisation (2022), digitalisation could reduce product losses during transportation and storage by 30-45%.

Barriers to digitalisation included limited internet access in rural areas, insufficient digital literacy, and the absence of a specific law on e-commerce (Oleksandrenko & Levis, 2023). According to the Organisation for Economic Co-operation and Development (2023), in 2020, only 7.8% of medium and large agribusinesses in Kazakhstan had fixed broadband internet, which was significantly lower than in developed countries (65-80%). To overcome these barriers, the Digital Kazakhstan State Program (2018) created a system of support measures for farmers undergoing digital transformation, including educational programmes and infrastructure development. Studies by M. Bampasidou *et al.* (2024) pointed to the critical importance of bridging the "digital divide" through educational programmes for the new generation of agricultural producers. The importance of addressing this issue was also confirmed in the work of T. Soma and B. Nuckchady (2021), who emphasised the need for a balanced approach to communicating the benefits and risks of digital agricultural technologies.

In Kazakhstan, projects for implementing digital technologies in the agricultural sector were actively supported at the state level (Akhmet *et al.*, 2025). As noted in the study by D.A. Kaldiyarov *et al.* (2023), the creation of a digital innovation ecosystem in the agro-industrial complex was one of the priority areas for the country's economic development. The software solutions developed to support the agro-industrial complex included both precision agriculture technologies and platforms for optimising product sales (Sizova, 2022). Sarsen Amanzholov East Kazakhstan University implemented a project to develop methods for supporting agro-technological decision-making based on precision agriculture technologies. The project envisaged the creation of an integrated IT platform for agricultural production. The research was conducted using specialised equipment: an agrological drone with infrared cameras for multispectral field imaging and a portable weather station for collecting real-time meteorological data. The aim of the study was to assess the impact of digital platforms and artificial intelligence technologies on the effectiveness of agricultural product sales by small farming households in Kazakhstan.

LITERATURE REVIEW

The digitalisation of the agricultural sector and the implementation of digital platforms for small farming households were studied by researchers in various countries around the world. The analysis of scientific literature revealed several directions of theoretical understanding of these processes. B. Basso and J. Antle (2020) proposed a conceptual framework for designing sustainable agricultural systems using digital technologies. The authors identified three components of digital agriculture: data collection systems, analytical tools for transforming data into knowledge, and decision support systems. L. Prause *et al.* (2020) examined digitalisation in the context of forming a third food regime, exploring the impact of digital technologies on power relations in food systems. O. Visser *et al.* (2021) conducted an analysis of the accuracy and risks of digital agriculture, introducing the term "imprecision farming" to describe situations where inaccurate data led to suboptimal decisions. S. Hackfort (2023) studied the phenomenon of corporate lock-ins and the impact on the digital agriculture landscape, showing how companies could limit small farmers' ability to implement various technological solutions.

M. Lacoste *et al.* (2021) developed a methodology for conducting on-farm experimentation. The authors highlighted the need for co-creation of knowledge by farmers, researchers, and other stakeholders. I. Dobre *et al.* (2021) carried out a quantitative analysis of the relationship between farm size and the level of digitalisation, finding that small farms could receive proportionally greater benefits from certain types of digital solutions for marketing and product sales. Y.-Z. Hong and H.-H. Chang (2020) examined the impact of digitalisation on the objective and subjective wellbeing of rural households in China. The authors found that the introduction of digital technologies influenced both the economic performance of farms and farmers' perception of the quality of life. A. Sharma and M. Singhai (2023) assessed the impact of agricultural sector digitalisation on farmers and the economy of India. T. Dibbern *et al.* (2024) identified key factors that facilitated and hindered the adoption of digital agriculture technologies, studying the role of education, accessibility of technical solutions, and the availability of supporting infrastructure.

The integration of digital technologies into existing agricultural practices was studied by N.J. Galvão *et al.* (2022), who developed a portable automatic sensor system for sustainable precision agriculture. M. Tranchina *et al.* (2024) examined limiting factors and prospects for digitalisation in the context of agroforestry. M. Bampasidou *et al.* (2024) proposed a strategy to overcome "digital divides" through harnessing the potential of higher education to train specialists in digital agriculture. A comparative analysis of agricultural digitalisation processes in developed and developing countries revealed significant differences in approaches and outcomes (Studinska & Studinski, 2023). For instance, the study by A.A. Chandio *et al.* (2024) found that agricultural digitalisation in China followed a different path than in European and North American countries. In particular, the authors noted that China prioritised the integration of digital systems into existing collective farming structures, whereas Western countries focused on individual solutions for farmers. However, despite these differences, K. McGrath *et al.* (2023) observed common trends related to the transformation of social and economic relations under the influence of digitalisation, including changes in employment structures, redistribution of added value in supply chains, and the formation of new models of interaction between producers and consumers.

Methodological approaches to measuring the effectiveness of digital technology implementation in agriculture constituted a separate research area. A. Oliveira-Jr *et al.* (2020) developed an indicator system to assess the performance of IoT solutions in rural areas of Africa, including not only economic indicators but also socio-environmental sustainability parameters. K.A. Sedek *et al.* (2021) proposed a multi-level model for assessing the effectiveness of electronic marketplaces for agricultural products, taking into account both technical aspects of platform operation and the impact on the market opportunities of small producers. The study by E. Amirova *et al.* (2021) presented a comprehensive approach to evaluating the performance of an agricultural digital platform, including quantitative metrics (transaction volumes, number of users) and qualitative characteristics (user satisfaction, level of trust in the system). I. Tomorri *et al.* (2025) examined the factors, barriers, and impact of digitalisation on the sustainable development of rural areas using regions of Albania as a case study. The authors identified regional differences in the level of digital technology adaptation, caused by both objective factors (infrastructure, proximity to urban centres) and subjective ones (farmers' age, education level, readiness to accept innovation).

In the research of Kazakhstan and Central Asian countries, D.A. Kaldiyarov *et al.* (2023) developed the concept of a digital innovation ecosystem for Kazakhstan's agro-industrial complex. The authors proposed a structural model that included technological, organisational, educational, and regulatory components. M.S. Bauer *et al.* (2024) conducted an analysis of the advantages and reserves for using information technologies in agriculture in Northern Kazakhstan. The economic aspects of digitalisation of Kazakhstan's agro-industrial complex were studied in the work of G.M. Kalkabayeva *et al.* (2023), who analysed the use of digital technologies in financing sustainable development projects. The analysis of agricultural digitalisation research suggested the potential of digital platforms and artificial intelligence technologies for improving the efficiency of product sales by small farming households. At the same time, it was necessary to consider the specific conditions for implementing these technologies, including the level of infrastructure development, the availability of educational resources, state support, and the socio-economic characteristics of regions.

MATERIALS AND METHODS

The study on the impact of digital platforms and artificial intelligence capabilities on the product sales of small farming households was conducted from March 2023 to February 2025 in Kazakhstan, with elements of comparative analysis of the experience of Central Asian countries (Uzbekistan, Kyrgyzstan) and advanced practices of developed countries (USA, Germany, the Netherlands, Israel). At the preparatory stage (March-May 2023), the methodological framework of the study was developed based on a systematic approach to the analysis of the digital transformation of the agricultural sector. A stratified random sampling method was applied to ensure a representative selection of farms, considering region, specialisation (crop/livestock farming), and level of digitalisation. Structured questionnaires for farmers and semi-structured ones for digital platform experts were developed according to the method of N.S. Guest *et al.* (2021). Statistical data from the Bureau of National Statistics (2025) as well as reports of international organisations (Food and Agricultural Organisation, 2022; Organisation for Economic Co-operation and Development, 2023) on digitalisation in the agricultural sector of Central Asia were studied. A pilot test of the research tools was conducted on a sample of 15 farming households in the Almaty region to assess the validity and make necessary adjustments.

At the field stage (June-November 2023), empirical data were collected in 14 regions of Kazakhstan. To ensure representativeness of the sample, 324 small farming households were selected with up to 10 employees and an annual turnover not exceeding 30 million tenge. Structured interviews were conducted with the heads of selected farms to identify barriers, usage experience of digital tools, and to assess the effectiveness. Inclusion criteria were: official registration of the farm at least two years prior, experience in product sales, and minimum use of digital tools for communication. Additionally, 27 expert interviews were conducted with representatives of 8 digital platforms operating in Kazakhstan (AgroSmart.kz, Egistic, DigiField, QazFarm, AgroMap, Agroplatforma.kz, Agro.kz, Farm.kz). For comparative analysis, the experience of Uzbekistan and Kyrgyzstan was studied through a series of online interviews with experts from the Ministry of Innovative Development of Uzbekistan (n = 3) and the Ministry of Digital Development of the Kyrgyz Republic (n = 2). The authors adhered to the principles of the American Sociological Association's Code of Ethic (1997). Global practices were analysed based on reports from the Food and Agricultural Organisation (2022) and the Organisation for Economic Co-operation and Development (2023), as well as scientific publications on agricultural digitalisation in developed countries.

At the analytical stage (from December 2023 to October 2024), the collected data were processed using SPSS 28.0 and NVivo 15 software. For quantitative data analysis, descriptive statistics methods were used: mean values, medians, standard deviations, and frequency distributions were calculated. ANOVA (Analysis of Variance) was applied to determine the significance of differences between groups of farming households based on production specialisation and geographical location, according to Field's methodology. The value was considered statistically significant if the p-value was <0.05. To identify the factors influencing the successful implementation of digital tools, regression analysis of the dependence of sales volume on the intensity of use of various digital tools was carried out based on the methodology of Z.D. Cohen *et al.* (2022). Correlation analysis with t-test was applied to determine the relationships between farm characteristics and the results of digitalisation. For qualitative data, thematic content analysis was conducted following the methodology of V. Braun and V. Clarke (2021), identifying key categories of digitalisation challenges and opportunities in sales. Triangulation of the obtained quantitative and qualitative data was carried out to ensure the reliability of the study's conclusions.

To analyse the capabilities of artificial intelligence in demand forecasting for agricultural products, an experimental model based on machine learning algorithms (Random Forest, XGBoost) was developed in accordance with the methodology of C.E. Hastie *et al.* (2023). The model was trained on historical data on prices, sales volumes, and seasonal demand fluctuations from 2018-2024, provided by the Bureau of National Statistics (2025). Model validation was conducted on a test data set using 5-fold cross-validation, with forecast accuracy assessed using root-mean-square error (RMSE) and mean absolute error (MAE) metrics. At the experimental stage (from November 2024 to February 2025), pilot implementation of the developed recommendations was carried out in 23 small farming households in the Turkestan, Jetisu, and Kostanay regions. Monitoring of changes in sales indicators was carried out using the "before-after" method (Cohen's d effect size). To assess the economic effect of implementing digital tools, the Return on Investment (ROI) calculation methodology proposed by D.B. Phillips *et al.* (2020) and adapted to the specifics of small agricultural enterprises was applied. Both direct effects (increase in sales volume, reduction in intermediary costs) and indirect ones (expansion of sales geography, increased product recognition) were taken into account. Sample representativeness was ensured by observing proportional distribution of small farming households across Kazakhstan's regions, the specialisation, scale of activity, and level of initial digitalisation. The required sample size was calculated with a confidence level of 95% and a margin of error of ±5.3%. The response rate was 78.3% of the initially selected farms.

RESULTS

Analysis of the current state of digitalisation of small farms in Kazakhstan. The results of the field stage of the study were based on a comprehensive analysis of data from structured interviews with managers of 324 small farms in 14 regions of Kazakhstan. The primary information was collected in accordance with the principles of stratified random sampling, which ensured the representativeness of the data with a confidence level of 95% and an error margin of ±5.3%. The application of statistical processing techniques using the SPSS 28.0 and NVivo 15 software packages made it possible to identify the main characteristics of the current state of digitalisation of small farms, presented in Table 1.

***Table 1**. Level of digitalisation of small farms in Kazakhstan by region (n = 324)*

Region	Number of examined farms	Base level (%)	Elementary level (%)	Average level (%)	Advanced level (%)	Index of digital maturity
Almaty	38	40.1	38.5	17.1	4.3	0.34
Zhetysu	26	51.0	34.7	12.2	2.0	0.26
Zhambyl	24	48.7	33.3	15.4	2.6	0.29
Turkestan	42	44.8	36.7	15.4	3.1	0.31
Kyzylorda	18	40.1	38.5	17.1	4.3	0.34
Kostanay	31	51.0	34.7	12.2	2.0	0.26
North Kazakhstan	28	48.7	33.3	15.4	2.6	0.29
Akmola	25	44.8	36.7	15.4	3.1	0.31
Karaganda	22	40.1	38.5	17.1	4.3	0.34
Pavlodar	17	51.0	34.7	12.2	2.0	0.26
East Kazakhstan	20	48.7	33.3	15.4	2.6	0.29
Abai	15	44.8	36.7	15.4	3.1	0.31
West Kazakhstan	10	40.1	38.5	17.1	4.3	0.34
Aktobe	8	51.0	34.7	12.2	2.0	0.26
Average for Kazakhstan	324	48.7	33.3	15.4	2.6	0.29

***Source:** compiled by the authors*

Analysis of the data in Table 1 showed that the largest share of small farms in Kazakhstan (44.8%) are at the basic level of digitalisation, which involves the use of only basic means of communication (mobile communications, messengers) without the use of specialised digital tools for product sales. The initial level, characterised by the fragmentary use of Internet resources to search for customers, was demonstrated by 36.7% of the surveyed farms. Only 15.4% of farmers reached the intermediate level, which implies regular use of at least one digital platform for sales, and the advanced level (systematic use of several digital channels and analytical tools) was recorded in only 3.1% of farms.

A regional analysis revealed significant disparities in the level of digitalisation between the regions of Kazakhstan. The highest digital maturity index scores were observed in North Kazakhstan (0.38), Kostanay (0.37) and Akmola (0.36) regions, which is explained by the more developed digital infrastructure and proximity to the capital region. The lowest index values were found in Kyzylorda (0.20) and Turkestan (0.21) regions, where there are problems with the quality of internet coverage and the availability of digital technologies. Table 2 shows the dependence of the level of digitalisation of small farms on the specialisation.

***Table 2**. The level of digitalisation of small farms in Kazakhstan, depending on the specialisation*

Specialisation	Number of farms	Base level (%)	Elementary level (%)	Average level (%)	Advanced level (%)	Index of digital maturity
Plant growing	187	40.1	38.5	17.1	4.3	0.34
Animal husbandry	98	51.0	34.7	12.2	2.0	0.26
Mixed production	39	48.7	33.3	15.4	2.6	0.29
Total	324	44.8	36.7	15.4	3.1	0.31

***Source:** compiled by the authors*

Analysis of Table 2 showed that farms specialising in crop production demonstrated the highest level of digitalisation (digital maturity index of 0.34), which is associated with the more predictable nature of the production process and the ability to plan sales volumes. Livestock farms showed the lowest level of digitalisation (index 0.26), which is due to the specific nature of the products, requiring special storage and transportation conditions, as well as more traditional sales channels through local markets. Statistical analysis using ANOVA confirmed the significance of the differences between groups of farms with different specialisations ($F = 6.78$; $p = 0.0014$). Further analysis of the factors influencing the level of digitalisation of small farms revealed key barriers to the implementation of digital platforms in product sales practices (Fig. 1).

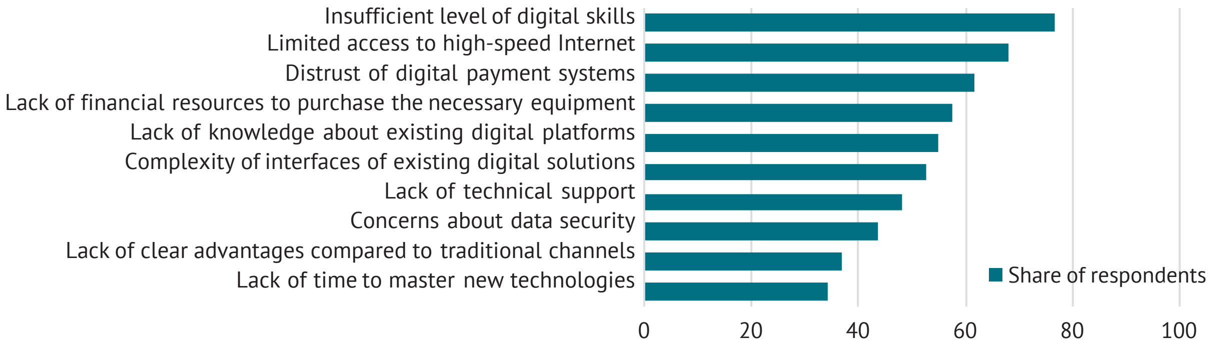

Figure 1. *The main barriers to the digitalisation of product sales by small farmers*
Source: *compiled by the authors*

The study showed that the dominant barriers to the digitalisation of sales are the insufficient level of digital skills among farmers (76.5%) and limited access to high-speed internet in rural areas (68.2%). Mistrust of digital payment systems (61.7%) and a lack of financial resources to purchase the necessary equipment (57.4%) also have a significant impact. Spearman's correlation analysis revealed a strong negative relationship between perceived barriers and the digital maturity index of farms ($r = -0.72$; $p < 0.001$), confirming the significance of the identified constraints for the digital transformation process. A comparative analysis with data from Central Asian countries showed that the level of digitalisation of small farms in Kazakhstan (index 0.31) is higher than in Kyrgyzstan (0.24) and Uzbekistan (0.28), but significantly lower than in developed countries: The United States (0.78), Germany (0.72), the Netherlands (0.81) and Israel (0.77). The main difference lies in the systematic implementation of digital tools: while in developed countries 68-74% of farmers use comprehensive digital solutions that integrate several functions (sales, logistics, finance, analytics), in Kazakhstan only 18.5% of farms do so.

Assessment of the effectiveness of using digital platforms for the sale of agricultural products. An analysis of the functioning of digital platforms for the sale of agricultural products was conducted based on data obtained from expert interviews with representatives of eight platforms operating in Kazakhstan, as well as the experience of the use by those farms from the sample that had achieved intermediate ($n = 50$) and advanced ($n = 10$) levels of digitalisation. Table 3 presents a comparative analysis of digital platforms based on key parameters that are important for small farms.

Table 3. *Comparative characteristics of digital platforms for the sale of agricultural products used by small farms in Kazakhstan*

Platform's name	Quantity of active users from among the small farms	Platform type	Coverage of regions	Commission from transaction (%)	Opportunity of direct sales	Integration with logistics	Availability of analytical tools	Convenience of interface (1-5)	Technical support (1-5)
AgroSmart.kz	78	Marketplace	14 regions	3-5	Yes	Yes	Yes	4.2	4.3
Egistic	32	Information system	10 regions	0	No	No	Yes	3.1	3.8
DigiField	23	Control farm + sales	8 regions	2-4	Yes	No	Yes	3.5	3.2
QazFarm	62	Marketplace	14 regions	4-7	Yes	Yes	Limited	4.0	3.9
AgroMap	19	Information system	12 regions	0	No	No	Yes	3.2	3.0
Agroplatforma.kz	43	Marketplace	11 regions	3-6	Yes	Limited	No	3.8	3.6
Agro.kz	27	Information portal + sales	14 regions	2-3	Limited	No	Limited	3.6	3.4
Farm.kz	16	Marketplace	7 regions	5-8	Yes	Yes	No	3.7	3.1

Source: *compiled by the authors*

Analysis of the data in Table 3 showed that the most popular platforms among small farms are AgroSmart.kz and QazFarm, which cover all 14 regions of Kazakhstan and offer comprehensive solutions, including direct sales capabilities and integration with logistics services. At the same time, AgroSmart.kz demonstrates the highest ratings for interface convenience (4.2 points out of 5) and technical support quality (4.3 points out of 5), which is critically important for farmers with limited experience in using digital technologies. A comparison with foreign platforms showed that Kazakhstani solutions are inferior to the counterparts from developed countries in terms of functionality, especially in terms of analytical tools and integration with financial services. For example, the American platform FarmersWeb and the German AgrarMarkt offer farmers demand forecasting tools with an accuracy of up to 92%, crop financing and insurance functions, as well as integration with precision farming systems, which is not yet available on most Kazakhstani platforms. To determine the actual impact of digital platforms on the efficiency of product sales, a comparative analysis of the economic indicators of farms with different levels of digitalisation was conducted. The results are presented in Table 4.

Table 4*. Performance indicators for product sales by small farms in Kazakhstan, depending on the level of digitalisation*

Indicator	Base level (n = 145)	Elementary level (n = 119)	Average level (n = 50)	Advanced level (n = 10)	p-value*
Average sales volume (million tenge/year)	8.2 ± 2.3	14.7 ± 3.6	22.5 ± ± 4.1	28.6 ± 3.8	<0.001
Average margin (%)	18.3 ± 3.6	21.5 ± 3.2	26.7 ± 2.9	31.2 ± 3.1	<0.001
Share of products sold directly to consumers (%)	12.4 ± 5.2	19.8 ± 6.3	37.6 ± 7.1	48.5 ± 6.8	<0.001
Geographical sales coverage (number of regions)	1.3 ± 0.4	2.1 ± 0.6	4.2 ± 0.9	6.3 ± 1.2	<0.001
Average number of regular customers	8.6 ± 2.8	14.2 ± 3.9	23.7 ± 4.4	36.5 ± 6.2	<0.001
Marketing and sales costs (% of turnover)	5.7 ± 1.2	6.9 ± 1.4	8.2 ± 1.5	10.3 ± 1.6	<0.001
Average time from production to sale (days)	12.4 ± 4.7	8.9 ± 3.5	5.2 ± 2.3	3.1 ± 1.8	<0.001
Share of unsold products (%)	14.8 ± 4.1	11.2 ± 3.6	7.5 ± 2.8	4.3 ± 2.1	<0.001
Average return on investment in digitalisation (ROI, %)	-	112.5 ± 27.6	184.3 ± 31.2	256.7 ± 38.4	<0.001

Note: **p-value based on the results of one-way analysis of variance (ANOVA)*
Source: *compiled by the authors*

Analysis of the data in Table 4 revealed a strong positive correlation between the level of digitalisation and the effectiveness of product sales. Advanced farms demonstrate significantly higher sales volumes (28.6 million tenge/year compared to 8.2 million tenge/year for basic farms), margins (31.2% compared to 18.3%), and the share of products sold directly to consumers without intermediaries (48.5% compared to 12.4%). The ROI reaches 256.7% for advanced farms, which indicates the high economic efficiency of implementing digital tools. Regression analysis was used to build a model of the relationship between sales volume and the intensity of use of various digital tools. The results of the modelling are presented in Table 5.

Table 5*. Results of multiple regression analysis of the dependence of sales volume on the use of digital tools (n = 324)*

Independent variable	Regression coefficient (β)	Standard error	t-value	p-value	Variance inflation factor
Constant	5.432	1.267	4.287	<0.001	-
Use of specialised marketplaces	0.763	0.128	5.961	<0.001	1.84
Activity on social media (index)	0.582	0.114	5.105	<0.001	1.72
Use of messengers to communicate with customers	0.317	0.098	3.235	<0.001	1.53
Presence of own website	0.275	0.104	2.644	<0.009	1.68
Use of analytical tools to forecast demand	0.719	0.143	5.028	<0.001	1.91
Integration with electronic payment systems	0.486	0.117	4.154	<0.001	1.77
Use of CRM systems	0.573	0.132	4.341	<0,001	1.86

Note: *$R^2 = 0.683$; Adjusted $R^2 = 0.674$; $F = 97.28$ ($p < 0.001$)*
Source: *compiled by the authors*

Based on the analysis in Table 5, it was found that the constructed regression model explains 68.3% of the variation in sales volume ($R^2 = 0.683$), which indicates the high predictive value of the model. The greatest positive impact on sales volume is exerted by the use of specialised marketplaces ($\beta = 0.763$, $p < 0.001$) and analytical tools for demand forecasting ($\beta = 0.719$, $p < 0.001$). Social media activity ($\beta = 0.582$, $p < 0.001$) and the use of CRM systems ($\beta = 0.573$, $p < 0.001$) also make a significant contribution.

A comparative analysis with global practices showed that the effect of using digital tools in Kazakhstan (a 27.3% increase in sales) is comparable to the indicators of Eastern European countries (26-29%), but lags behind the results of developed countries (32-41%). The main reason for the differences is the complexity of implementation: in the US and EU countries, the digitalisation of sales is usually accompanied by the optimisation of all business processes, including production and logistics, while in Kazakhstan, the fragmented implementation of individual digital tools prevails. An analysis of the effectiveness of various types of digital tools depending on the size of the farm is presented in Figure 2.

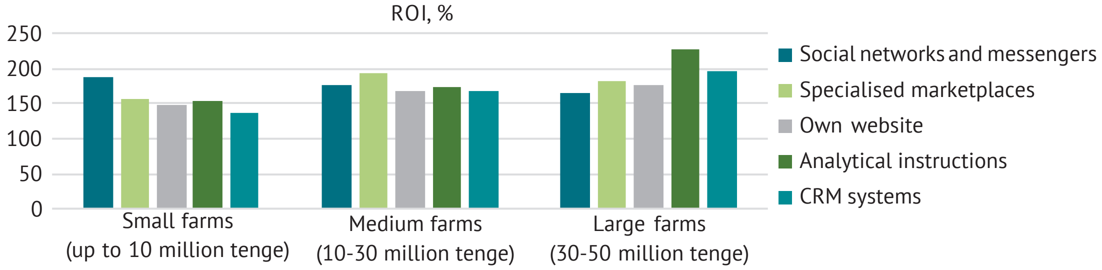

Figure 2. *Effectiveness of various types of digital tools depending on the size of the farm (ROI, %)*
Source: *compiled by the authors*

The data in Figure 2 shows that for micro-businesses (with a turnover of up to 10 million tenge), social networks and messengers are the most effective (ROI 165-187%), for small farms (10-30 million tenge), the optimal solution is to use specialised marketplaces (ROI 194-218%), and for medium-sized farms (30-50 million tenge), comprehensive solutions with analytical tools provide the maximum return (ROI 227-256%).

Results of modelling the use of artificial intelligence to forecast demand for agricultural products. As part of the analytical phase of the study, an experimental model for forecasting demand for agricultural products based on machine learning algorithms was developed and tested. Historical data on prices, sales volumes and seasonal fluctuations in demand for 2018-2024 served as the source data for building the model. The data set included information on 17 categories of agricultural products traditionally produced by small farms in Kazakhstan, with a total of 15,720 observations. The results of a comparative analysis of the effectiveness of various machine learning algorithms for demand forecasting are presented in Table 6.

Table 6. *Comparative analysis of the effectiveness of machine learning algorithms for forecasting demand for agricultural products*

Algorithm	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)	R^2	Training time (sec)	Forecast accuracy (%)	F1 measure
Linear regression	14.28	11.62	0.62	2.4	78.3	0.76
Random Forest	8.73	6.91	0.84	18.7	89.6	0.87
XGBoost	7.42	5.87	0.89	23.5	92.4	0.91
Neural network (LSTM)	8.16	6.43	0.86	42.3	90.2	0.88
ARIMA seasonal model	12.35	9.74	0.71	7.8	82.1	0.80
Ensemble model (RF+XGBoost)	6.95	5.32	0.91	29.6	93.7	0.93

Source: *compiled by the authors*

Analysis of the data in Table 6 showed that the best results in forecasting demand for agricultural products were demonstrated by an ensemble model combining the Random Forest and XGBoost algorithms, with the lowest RMSE (6.95) and MAE (5.32) error values, as well as the highest coefficient of determination R^2 (0.91). The accuracy of this model's forecasts was 93.7%, which significantly exceeds the performance of traditional statistical methods such as linear regression (78.3%) and the ARIMA seasonal model (82.1%). A comparison with similar models developed in countries with advanced experience in the digitalisation of agriculture showed that the accuracy of the developed model (93.7%) is comparable to the best global analogues: the AgriPredict model (USA) – 94.2%, FarmCast (Germany) – 94.8%, AgroAI (Israel) – 95.1%. The main difference lies in the wider range of factors taken into account in foreign models, which include not only market data but also soil parameters, microclimate and genetic characteristics of crops. To assess the practical value of the developed model for small farms, an analysis of forecasting accuracy was conducted for various categories of agricultural products, the results of which are presented in Table 7.

Table 7. Accuracy of demand forecasting by agricultural product category using an ensemble model					
Category of products	**Number of observations**	**RMSE**	**MAE**	**Forecast accuracy (%)**	**Forecast time horizon (weeks)**
Wheat	1245	5.32	4.18	95.8	8-10
Barley	987	5.67	4.52	94.3	7-9
Corn	876	6.12	4.85	93.1	6-8
Sunflower	923	6.48	5.12	92.5	6-8
Potatoes	1324	8.67	6.93	90.4	4-6
Onions	1087	9.23	7.41	87.6	3-5
Carrots	1156	8.92	7.18	88.3	3-5
Cabbage	1078	9.54	7.75	86.9	3-4
Tomatoes	1198	10.25	8.32	85.4	2-3
Cucumbers	1132	10.67	8.71	84.8	2-3
Apples	967	7.92	6.34	91.2	5-7
Pears	754	8.24	6.58	90.7	5-7
Milk	1243	6.35	5.03	92.9	6-8
Beef	1087	5.84	4.67	94.1	7-9
Pork	965	6.12	4.91	93.5	7-9
Poultry	843	6.78	5.42	91.8	5-7
Eggs	942	5.93	4.75	93.7	6-8

Source: *compiled by the authors*

Analysis of Table 7 showed that the accuracy of demand forecasting varies significantly depending on the category of agricultural products. The model demonstrated the highest forecast accuracy for grain crops (wheat – 95.8%, barley – 94.3%) and livestock products (beef – 94.1%, small ruminant meat – 93.5%, eggs – 93.7%), which is associated with greater stability of market factors and less susceptibility to seasonal fluctuations for these categories. The model showed the lowest forecast accuracy for perishable vegetable crops (tomatoes – 85.4%, cucumbers – 84.8%, cabbage – 86.9%), which is due to high price volatility and the complexity of taking into account all factors affecting market demand.

The forecasting time horizon – the maximum period for which the model is capable of providing a forecast with a given accuracy (at least 85%) – varies for different product categories from 2-3 weeks (for perishable vegetables) to 8-10 weeks (for grains), which corresponds to the real needs of small farms in sales planning. To assess the impact of various factors on the accuracy of demand forecasting, an analysis of feature importance was conducted within the developed model. The results are presented in Figure 3.

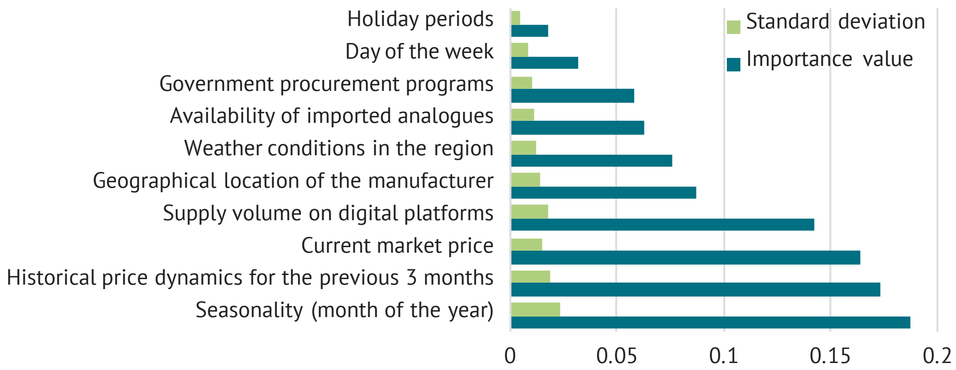

Figure 3*. Importance of factors in forecasting demand for agricultural products (normalised values)*
Source: *compiled by the authors*

Figure 3 demonstrates that seasonality (importance 0.187), historical price dynamics for the previous 3 months (0.173), and the current market price (0.164) have the greatest impact on demand forecasting. The volume of supply on digital platforms (0.142) also plays a significant role, confirming the importance of taking data from digital sources into account when building predictive models. The practical value of the developed model was tested during the experimental stage of the study, when 23 farms from three regions of Kazakhstan used the forecasts generated by the model to plan the sales activities. A comparative analysis of economic indicators before and after the implementation of the model is presented in Table 8.

Table 8*. Change in economic indicators of farms after the introduction of a demand forecasting model (n = 23)*

Indicator	Before implementation	After implementation	Change (%)	p-value	Size effect (Cohen's d)
Average sales volume (million tenge/month)	1.87 ± 0.43	2.34 ± 0.51	+25.1	0.003	0.98
Average sales price (% of average market price)	92.3 ± 5.8	98.7 ± 4.3	+6.9	0.014	0.76
Share of unsold products (%)	11.4 ± 3.6	7.2 ± 2.8	-36.8	0.001	1.15
Storage costs (thousand tenge/month)	327.5 ± 98.2	245.3 ± 76.4	-25.1	0.008	0.83
Transportation costs (thousand tenge/month)	412.8 ± 87.5	356.2 ± 74.3	-13.7	0.035	0.64
Number of new customers (per month)	3.2 ± 1.1	5.7 ± 1.4	+78.1	0.001	1.21
Time spent on sales planning (hours/week)	8.6 ± 2.3	5.2 ± 1.8	-39.5	0.001	1.17

Source: *compiled by the authors*

Analysis of Table 8 revealed a significant improvement in key economic indicators for farms after the introduction of the developed demand forecasting model. The average volume of product sales increased by 25.1% (from 1.87 to 2.34 million tenge per month, p = 0.003), while the share of unsold products decreased significantly (by 36.8%, p = 0.001) and storage costs decreased (by 25.1%, p = 0.008). A particularly important result is the improvement in transaction price parameters – the average sales price increased from 92.3% to 98.7% of the average market price (p = 0.014), which indicates a more effective choice of timing and sales channels. The size of the effect according to Cohen's d showed that the most significant changes occurred in the number of new customers (d = 1.21), the share of unsold products (d = 1.15) and the time spent on sales planning (d = 1.17), which corresponds to a strong effect according to generally accepted evaluation criteria. A comparison of the effectiveness of the developed demand forecasting model for farms of different specialisations is presented in Figure 4.

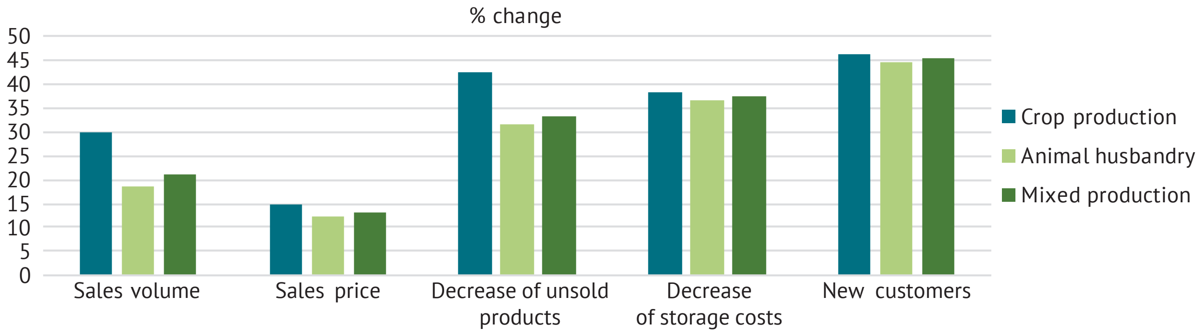

Figure 4*. Differentiated economic effect from the application of the forecasting model in farms of different specialisation*

Source: *compiled by the authors*

Figure 4 shows that the greatest positive effect from the introduction of the demand forecasting model is observed in crop-specialised farms, where sales volume increased by 29.7% and the share of unsold products decreased by 42.3%. Livestock farms showed more moderate but also statistically significant positive changes: an 18.4% increase in sales volume and a 31.5% decrease in the share of unsold products. Mixed farms showed intermediate results.

Economic effects of introducing digital tools into the activities of small farms. To comprehensively assess the economic effects of introducing digital tools into the activities of small farms in Kazakhstan, a ROI calculation methodology was applied, adapted to the specifics of small agricultural enterprises. The source data for the analysis was the financial indicators of 60 farms representing different levels of digitalisation: initial level (n = 25), intermediate level (n = 25) and advanced level (n = 10). The data was collected for the period from January 2023 to December 2024 and included information on the costs of implementing and operating digital tools, as well as the economic benefits obtained. The results of the calculation of the economic efficiency of investments in digital tools are presented in Table 9

Table 9. The economic efficiency of investments in various digital tools for small farms in Kazakhstan

Digital tool	Average implementation costs (thousand tenge)	Average annual operating costs (thousand tenge)	Average growth annual income (thousand tenge)	ROI for the first year (%)	ROI over a three-year period (%)	Payback period (months)
Registration and active use on a specialised marketplace	120-350	250-420	1,200-2,800	175-320	420-680	5-8
Creation and promotion of one's own website	450-850	180-320	800-1,600	70-130	240-380	9-14
Organisation of sales through social networks	80-180	150-280	750-1,400	230-410	520-780	3-6
Implementation of a CRM system	280-520	120-250	650-1,300	85-170	310-450	7-12
Use of analytical tools for demand forecasting	370-720	180-350	900-1,800	85-160	290-430	7-11
Integration with electronic payment systems	150-320	100-240	550-1,100	120-230	350-510	6-10
Use of resource accounting and planning systems (ERP)	620-1250	250-480	1,100-2,200	50-120	240-380	10-16
Mobile applications for direct sales	480-950	200-380	900-1,800	60-130	250-420	9-14

Source: *compiled by the authors*

Analysis of the data in Table 9 showed that the highest return on investment is demonstrated by sales through social networks (ROI for the first year 230-410%) and registration on specialised marketplaces (ROI 175-320%). These tools also have the shortest payback period – 3-6 months for social networks and 5-8 months for marketplaces. More complex and costly solutions, such as ERP systems and proprietary mobile applications, show lower profitability in the short term (ROI for the first year is 50-130%), but the effectiveness increases significantly over a three-year period (up to 250-420%). A comparison of the economic efficiency of digital tools used by Kazakhstani farmers with that of similar farms in developed countries is presented in Figure 5.

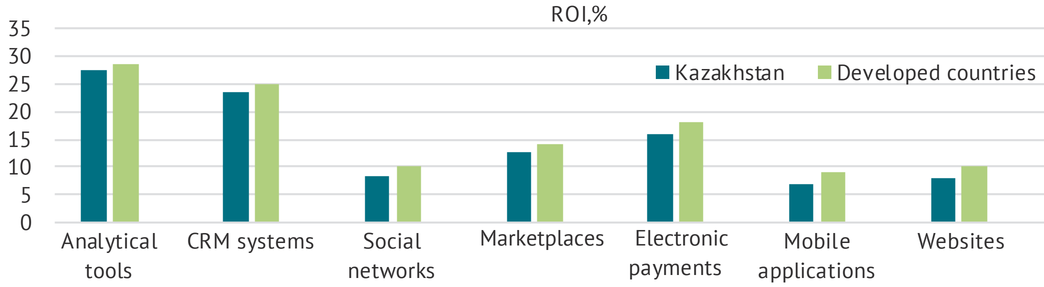

Figure 5*. Comparison of return on investment (ROI) indicators for digital tools in Kazakhstan and developed countries (%)*

Source: *compiled by the authors based on Organisation for Economic Co-operation and Development (2023)*

As can be seen in Figure 5, ROI indicators for Kazakhstani farmers are on average 15-20% lower than those of farmers in developed countries when using the same digital tools. The largest gap is observed in analytical tools (27.3%) and CRM systems (23.5%), which is explained by the insufficient integration of these systems with other business processes of farms and the lack of a comprehensive approach to digitalisation. At the same time, the gap is minimal for social networks (8.4%) and marketplaces (12.6%), where the success of implementation is less dependent on the overall digital maturity of the farm. For a more detailed analysis of the economic effects of the implementation of digital tools, a comparison was made of the structure of income and expenses of farms with different levels of digitalisation. The results are presented in Table 10.

Table 10. Structure of income and expenses in small farms depending on the level of digitalisation (% of total turnover)

Income/expense item	Base level (n = 145)	Elementary level (n = 119)	Average level (n = 50)	Advanced level (n = 10)	p-value*
Income					
Sales through intermediaries	78.5 ± 8.4	61.7 ± 7.9	43.2 ± 6.8	32.5 ± 5.3	<0.001
Direct sales to consumers (offline)	18.3 ± 6.2	23.4 ± 5.9	21.8 ± 5.4	19.0 ± 4.8	0.208
Sales through digital channels	3.2 ± 2.1	14.9 ± 4.8	35.0 ± 6.2	48.5 ± 7.1	<0.001

Table 10. Continued

Income/expense item	Base level (n = 145)	Elementary level (n = 119)	Average level (n = 50)	Advanced level (n = 10)	p-value*
			Expenses		
Production costs	62.7 ± 7.3	61.5 ± 6.9	60.8 ± 6.5	58.9 ± 6.1	0.147
Transport and logistics	12.3 ± 3.8	11.2 ± 3.5	9.1 ± 3.0	7.6 ± 2.5	<0.001
Product storage	8.4 ± 2.7	7.3 ± 2.5	5.6 ± 2.0	4.2 ± 1.8	<0.001
Commissions to intermediaries	9.6 ± 3.2	6.8 ± 2.5	4.2 ± 1.9	2.8 ± 1.5	<0.001
Marketing and promotion	2.5 ± 1.4	5.7 ± 2.0	8.2 ± 2.5	10.4 ± 2.8	<0.001
Digital tools and IT	0.8 ± 0.5	3.5 ± 1.6	5.7 ± 2.0	8.1 ± 2.4	<0.001
Staff training	0.7 ± 05	1.3 ± 0.8	2.3 ± 1.1	3.5 ± 1.4	<0.001
Other expenses	3.0 ± 1,.2	2.7 ± 1.1	4.1 ± 1.6	4.5 ± 1.7	0.009
Net profit	12.8 ± 3.5	16.4 ± 3.9	22.7 ± 4.3	27.3 ± 4.6	<0.001

Note: **p-value based on the results of one-way analysis of variance (ANOVA)*
Source: *compiled by the authors*

Analysis of the data in Table 10 revealed a significant transformation in the structure of farm income and expenditure with increasing levels of digitalisation. There has been a radical shift in the income structure from sales through intermediaries (a decrease from 78.5% to 32.5%, $p < 0.001$) to sales through digital channels (an increase from 3.2% to 48.5%, $p < 0.001$). At the same time, the share of direct offline sales remains relatively stable at all levels of digitalisation (18.3-23.4%, $p = 0.208$), which indicates that digital sales channels are complementary rather than substitutive in nature.

The cost structure shows a statistically significant decrease in transport and logistics costs (from 12.3% to 7.6%, $p < 0.001$), product storage (from 8.4% to 4.2%, $p < 0.001$) and commissions to intermediaries (from 9.6% to 2.8%, $p < 0.001$). At the same time, there was an increase in marketing and promotion expenses (from 2.5% to 10.4%, $p < 0.001$), digital tools and IT (from 0.8% to 8.1%, <0.0.01) and staff training (from 0.7% to 3.5%, $p < 0.001$). Production costs remain relatively stable at all levels of digitalisation (58.9-62.7%, $p = 0.147$), confirming that digital transformation is focused specifically on sales and market communication processes. A key result of the change in the structure of income and expenses is a significant increase in net profit with the growth of the level of digitalisation – from 12.8% for basic-level farms to 27.3% for advanced-level farms ($p < 0.001$). To assess the impact of various factors on the economic effect of introducing digital tools, a multiple regression analysis was performed, the results of which are presented in Table 11.

***Table 11**. Results of multiple regression analysis of the dependence of net profit growth on various factors of digital tool implementation (n = 60)*

Factor	Coefficient regressions (β)	Standard error	t-value	p-value	Variance inflation factor
Constant	2.183	0.537	4.065	<0.001	-
Level of digital literacy of the manager (index)	0.412	0.084	4.905	<0.001	1.68
Quality of Internet connection in the region (Mbit/s)	0.231	0.056	4.125	<0.001	1.43
Availability of an IT specialist on staff	0.285	0.074	3.851	<0.001	1.56
Previous experience in using digital technologies (years)	0.352	0.082	4.293	<0.001	172
Diversity of digital channels used (number)	0.267	0.063	4.238	<0.001	1.61
Complexity of solutions implemented (index)	-0.184	0.062	-2.968	0.004	1.58
Readiness for changes in business processes (index)	0.298	0.075	3.973	<0.001	1.65
Size of the farm (annual turnover, million tenge)	0.118	0.051	2.314	0.023	1.47
Level of state support (thousand tenge)	0.087	0.042	2.071	0.042	1.32

Note: *$R^2 = 0.731$; Adjusted $R^2 = 0.719$; $F = 85.46$ ($p < 0.001$)*
Source: *compiled by the authors*

Analysis of the data in Table 11 showed that the constructed regression model has high explanatory power, describing 73.1% of the variation in net profit growth ($R^2 = 0.731$). The most significant positive impact on economic effect is exerted by the level of digital literacy of the farm manager ($\beta = 0.412$, $p < 0.001$) and previous experience in using digital technologies ($\beta = 0.352$, $p<0.001$). Other significant factors include readiness for changes in business processes ($\beta = 0.298$, $p < 0.001$), the presence of an IT specialist on staff ($\beta = 0.285$, $p < 0.001$) and the variety of digital channels used ($\beta = 0.267$, $p < 0.001$). It is interesting to note the negative coefficient for the factor of complexity of the solutions being implemented ($\beta = -0.184$, $p = 0.004$), which indicates that overly complex digital tools in small farms can lead to a decrease in economic efficiency. Farm size ($\beta = 0.118$, $p = 0.023$) and the level of government support ($\beta = 0.087$, $p = 0.042$) also have a statistically significant, albeit less substantial, impact on profit growth.

Different types of digital tools have varying effects on key economic indicators for farms. Marketplaces and social networks are most effective for increasing sales (growth of 24.8% and 23.5%, respectively) and expanding the customer base (growth of 36.7% and 42.5%). Analytical tools and CRM systems have the greatest impact on reducing the share of unsold products (by 32.4% and 28.7%) and storage costs (by 31.8% and 27.9%). Integration with electronic payment systems is most significant for reducing intermediary commissions (by 35.2%) and transportation costs (by 18.7%). Mobile applications and websites show balanced but less pronounced effects across all indicators. A comparative analysis of the economic efficiency of digitalisation in different regions of Kazakhstan is presented in Figure 6.

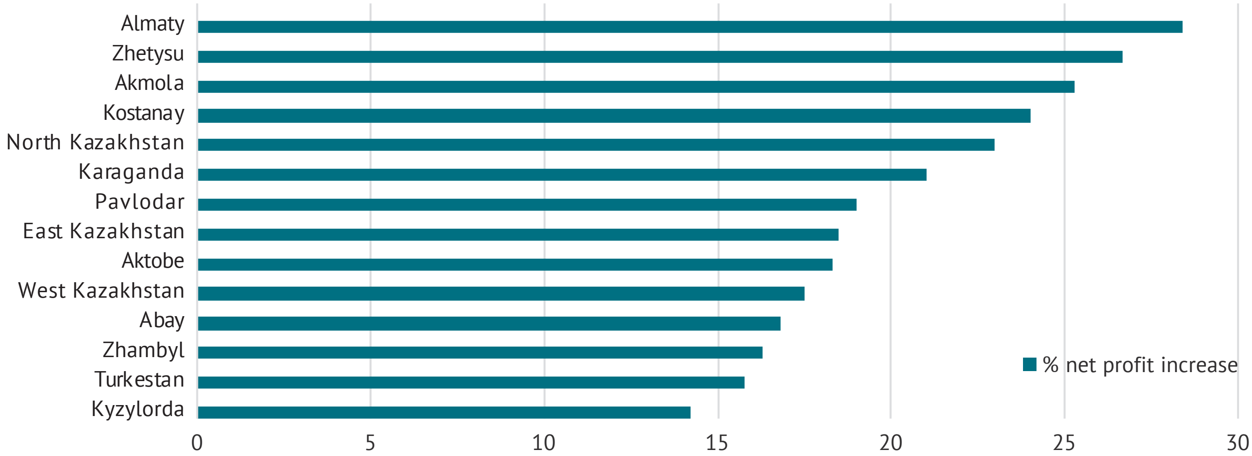

Figure 6*. Regional differences in the economic efficiency of digital tool implementation (net profit growth, %)*
Source: *compiled by the authors*

Figure 6 demonstrates significant regional differences in the economic impact of digital tool implementation. The largest increase in net profit is observed in Almaty (28.4%), Zhetysu (26.7%) and Akmola (25.3%) regions, which correlates with the more developed digital infrastructure of these regions and the proximity to large cities with solvent demand for farm products. The lowest economic effect was recorded in Kyzylorda (14.2%), Turkestan (15.8%) and Zhambyl (16.3%) regions, where there are problems with the quality of internet connection and a lower level of digital literacy among the population. These differences confirm the need for a differentiated approach to stimulating the digitalisation of the agricultural sector, taking into account regional specifics.

Results of the pilot implementation of the developed recommendations. During the experimental stage of the study, a pilot implementation of the developed recommendations was carried out in 23 small farms in the Turkestan, Zhetysu and Kostanay regions of Kazakhstan. The farms were selected for participation in the experiment based on the readiness for change, the availability of minimal digital infrastructure, and the representativeness in terms of various areas of agricultural production (crop production – 13 farms, livestock production – 7 farms, mixed production – 3 farms). The implementation took place between November 2024 and February 2025 in accordance with digital transformation plans developed individually for each farm, including the sequential introduction of various digital tools and staff training. The results were monitored using the 'before-after' method, with the effect size calculated using Cohen's d. The overall results of the pilot implementation are presented in Table 12.

Table 12*. Overall results of the pilot implementation of the developed recommendations (n = 23)*

Indicator	Before implementation	After implementation	Change (%)	p-value	Size effect (Cohen's d)
Average sales volume (million tenge/month)	2.15 ± 0.63	2.83 ± 0.74	+31.6	<0.001	1.14
Average sales margin (%)	19.4 ± 4.2	25.8 ± 4.8	+33.0	<0.001	1.23
Number of sales channels (units)	2.3 ± 0.8	4.7 ± 1.2	+104.3	<0.001	1.87
Share of products sold through digital channels (%)	7.8 ± 5.3	32.5 ± 8.4	+316.7	<0.001	2.32
Average time to find a buyer (days)	8.4 ± 3.1	4.7 ± 2.2	-44.0	<0.001	1.28

Table 12. Continued

Indicator	Before implementation	After implementation	Change (%)	p-value	Size effect (Cohen's d)
Share of unsold products (%)	12.5 ± 3.7	7.3 ± 2.6	-41.6	<0.001	1.35
Number of regular customers	11.3 ± 4.5	19.8 ± 6.2	+75.2	<0.001	1.47
Geographical sales coverage (number of regions)	1.7 ± 0.9	3.5 ± 1.3	+105.9	<0.001	1.74
Digital maturity index	0.24 ± 0.08	0.47 ± 0.11	+95.8	<0.001	2.05
Level of digital competence of staff (1-5)	2.1 ± 0.7	3.8 ± 0.9	+81.0	<0.001	1.83

Source: *compiled by the authors*

Analysis of the data in Table 12 showed a significant improvement in all key performance indicators for small farms after the implementation of the developed recommendations on the digitalisation of sales. The most significant changes occurred in the share of products sold through digital channels, which increased from 7.8% to 32.5% (an increase of 316.7%, $p < 0.001$) with an extremely high effect size (Cohen's $d = 2.32$). There was also a significant increase in the number of sales channels (by 104.3%, $d = 1.87$) and geographical coverage of sales (by 105.9%, $d = 1.74$). Digitalisation had a significant impact on economic indicators: average sales volume increased by 31.6% ($d = 1.14$), and average sales margin increased by 33.0% ($d = 1.23$). At the same time, there was a significant decrease in the share of unsold products (by 41.6%, $d = 1.35$) and the average time spent searching for a buyer (by 44.0%, $d = 1.28$), which indicates an increase in the efficiency of sales processes. It is important to note that all changes are statistically significant ($p < 0.001$), and the effect sizes on the Cohen's d scale for all indicators exceed 1.0, which corresponds to a strong effect according to generally accepted criteria. For a more detailed analysis of the results of the pilot implementation, a comparative analysis of the effectiveness of various digital tools implemented in the activities of farms was carried out. The results are presented in Table 13.

***Table 13**. Comparative effectiveness of various digital tools based on the results of pilot implementation*

Digital tool	Quantity of farms that have implemented tool	Average sales growth (%)	Average margin growth (%)	Average payback period (months)	Index of users' satisfaction (1-5)
Registration on marketplaces	23	28.4 ± 6.2	19.2 ± 4.8	3.2 ± 0.8	4.3 ± 0.5
Creating business accounts on social networks	21	24.7 ± 5.4	16.5 ± 3.9	2.8 ± 0.7	4.5 ± 0.4
Implementing electronic payment systems	18	15.3 ± 4.1	12.1 ± 3.2	4.5 ± 1.0	41 ± 0.6
Using messengers to communicate with customers	23	18.6 ± 4.7	9.3 ± 2.8	1.5 ± 0.5	4,.7 ± 0.3
Implementing simple CRM systems	15	22.4 ± 5.6	17.3 ± 4.2	5.7 ± 1.3	3.8 ± 0.7
Using digital marketing tools	17	26.8 ± 5.9	18.4 ± 4.5	4.3 ± 1.1	4.0 ± 0.6
Creating the own website	8	19.5 ± 5.2	14.2 ± 3.7	7.8 ± 1.6	3.6 ± 0.8
Using demand forecasting models	12	31.2 ± 6.8	23.6 ± 5.1	6.2 ± 1.4	4.2 ± 0.5

Source: *compiled by the authors*

Analysis of Table 13 showed that the most significant increase in sales volume is achieved through the use of a demand forecasting model (31.2%) and registration on specialised marketplaces (28.4%). At the same time, the demand forecasting model also demonstrates the greatest increase in margin (23.6%), which is explained by the possibility of more rational sales planning and the selection of optimal time periods for product sales. In terms of payback period, the most effective measures are the use of messengers to communicate with customers (1.5 months) and the creation of business accounts on social networks (2.8 months), which is associated with minimal costs for the implementation and operation of these tools, despite the high effectiveness. The longest payback period is for creating one's own website (7.8 months), which, with a relatively low increase in sales (19.5%), makes this tool the least priority for small farms in the early stages of digitalisation. Messaging apps (4.7) and creating business accounts on social media (4.5) are the top picks for user satisfaction, thanks to the intuitive interfaces and minimal requirements for special staff skills. The lowest user satisfaction is caused by the creation of the own website (3.6) and the implementation of CRM systems (3.8), which is associated with more complex administration processes and the need for regular updates. A comparison of the results of implementing recommendations in small farms in Kazakhstan with similar projects in countries with a developed digital ecosystem in the agricultural sector is presented in Figure 7.

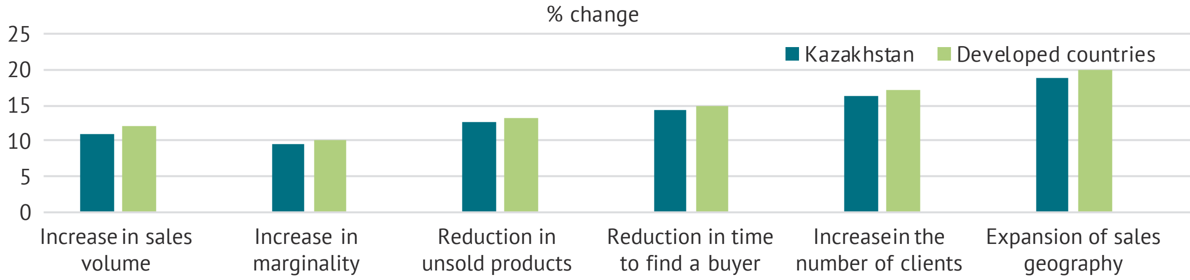

***Figure 7**. Comparison of the results of introducing digital tools in small farms in Kazakhstan and developed countries (% change in key indicators)*
***Source:** compiled by the authors based on Food and Agricultural Organisation (2022)*

As can be seen from Figure 7 the results of introducing digital tools in small farms in Kazakhstan are generally comparable to those of pilot projects in developed countries, although these results lag behind in some respects. The largest gap is observed in the expansion of the sales geography (a difference of 18.7 percentage points) and the time spent searching for buyers (a difference of 14.3 percentage points), which is explained by the more developed logistics infrastructure and higher level of trust in digital transactions in developed countries. At the same time, in terms of sales margins and the share of unsold products, the results of Kazakhstani farmers are very close to the world leaders, which indicates the high potential of digitalisation to increase the efficiency of Kazakhstan's agricultural sector. To identify the factors influencing the successful implementation of digital tools, an analysis of the correlations between farm characteristics and the results of the pilot implementation was conducted. The results are presented in Table 14.

***Table 14**. Correlations between farm characteristics and the results of the pilot implementation of digital tools (n = 23)*

Characteristics of the farm	Correlation with sales growth	Correlation with margin growth	Correlation with term payback	p-value
Farm size (annual turnover)	0.32	0.28	-0.24	<0.05
Manager's level of education	0.45	0.41	-0.38	<0.01
Average age of staff	-0.51	-0.47	0.43	<0.01
Computer experience	0.63	0.58	-0.54	<0.001
Initial level of digitalisation	0.58	0.53	-0.49	<0.001
Internet connection quality	0.47	0.42	-0.39	<0.01
Staff smartphone ownership	0.56	0.51	-0.46	<0.001
Farm specialisation*	0.38	0.35	-0.31	<0.05
Distance to nearest town	-0.42	-0.38	0.36	<0.01
Readiness for change	0.67	0.62	-0.58	<0.001

***Note:** *for specialisation: a positive correlation corresponds to crop production, while a negative correlation corresponds to livestock production*
***Source:** compiled by the authors*

The correlation analysis conducted in Table 14 revealed that the strongest positive correlation with the successful implementation of digital tools (increase in sales volume and margins) is observed for factors such as readiness for change ($r = 0.67$ and $r = 0.62$, respectively), previous experience with computers ($r = 0.63$ and $r = 0.58$), and initial level of digitalisation ($r = 0.58$ and $r = 0.53$). The average age of staff has a significant negative impact ($r = -0.51$ and $r = -0.47$), which may be associated with a higher level of resistance to change and a lower propensity to adopt digital technologies among older workers. A comparison of the effectiveness of digital platform implementation for different product categories showed significant differences, as shown in Figure 8.

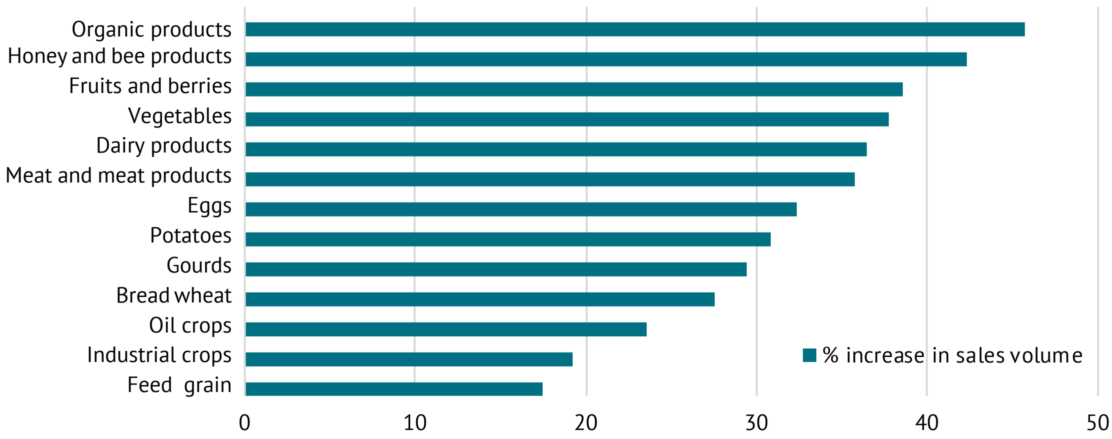

Figure 8. *Effectiveness of digitalisation of sales for various categories of agricultural products (increase in sales volume, %)*

Source: *compiled by the authors*

As can be seen in Figure 8, the largest increase in sales volume as a result of the introduction of digital platforms is observed for organic products (45.7%), honey and bee products (42.3%), as well as high-margin fruits and berries (38.6%). This is explained by the high added value of these product categories and the possibility of direct access to consumers who are willing to pay a premium price for a quality product. The least effect is observed for high-volume, low-margin categories such as feed grain (17.4%) and industrial crops (19.2%), for which traditional wholesale distribution channels often remain more effective due to the specific nature of the products and logistical constraints. Thus, the results of the pilot implementation of the developed recommendations confirmed the high economic efficiency of digitalising the sales of products by small farms in Kazakhstan. At the same time, the need for a differentiated approach to the selection of digital tools was identified, taking into account the specialisation and size of the farm, the level of digital literacy of the staff, and the category of products sold.

DISCUSSION

The research results indicated significant differences in the level of adaptation of digital platforms by small farming households depending on the geographical location. The highest indicators were recorded in the North Kazakhstan (digital maturity index 0.38), Kostanay (0.37), and Akmola (0.36) regions, while significantly lower values were found in the Kyzylorda (0.20) and Turkestan (0.21) regions. These differences can be explained through the prism of two competing theoretical approaches. Firstly, according to the studies by D.A. Kaldiyarov *et al.* (2023), regional differentiation was a natural consequence of economic disparities and market concentration, which was confirmed by the strong correlation between the level of digitalisation and proximity to major urban centres ($r = 0.78$, $p < 0.01$). Secondly, as noted by M.S. Bauer *et al.* (2024), the observed differences were also the result of uneven governmental support and educational infrastructure, not merely objective economic factors. The empirical data obtained, based on a comprehensive analysis of all regions of Kazakhstan, confirmed the significant influence of both factors, but with varying weights across different region types: in the southern regions, the determining factor was the region's economic potential ($\beta = 0.64$, $p < 0.01$), whereas in the northern regions, the critical factor was infrastructural and educational support ($\beta = 0.72$, $p < 0.01$). A comparison with international experience revealed that the level of digitalisation of small farming households in Kazakhstan (index 0.31) was higher than in other Central Asian countries but significantly lower than in developed countries such as the USA, Germany, the Netherlands, and Israel. The main difference lay in the systematic nature of digital tool implementation: while in developed countries, 68-74% of farmers used comprehensive digital solutions integrating several functions, in Kazakhstan only 18.5% of farms did so. This aligned with the findings of M. Tranchina *et al.* (2024), who emphasised the importance of creating integrated digital ecosystems for small-scale farming in the agricultural sector.

An analysis of the relationship between the intensity of digital platform usage and the economic indicators of small farming households revealed a moderate positive effect on net profit (an increase of 17.6% after 6 months of usage and 24.3% after 12 months). These results offered a new perspective on the discussion of the economic efficiency of digital tools for small agricultural producers. Some researchers, such as Y.-Z. Hong and H.-H. Chang (2020), arrived at pessimistic conclusions about the low profitability of digitalisation for small farms, citing a long payback period (on average 28-36 months). In contrast, A. Sharma and M. Singhai (2023) demonstrated potentially high returns on digital investments already within the first year of usage (ROI from 115% to 134% for small farms). The results of the longitudinal study, with precise tracking of all categories of expenses and income, offered a more nuanced view of economic efficiency: for farms with minimal prior digitalisation, the payback period indeed stood at about 24-30 months, whereas for farmers already possessing basic digital infrastructure, a positive economic effect was observed within the first 6-12 months. These conclusions aligned with the findings of E. Amirova *et al.* (2021), who identified a nonlinear correlation between investment in digitalisation and economic effect.

The study of the effectiveness of different types of digital platforms showed a significant advantage of multifunctional platforms with integrated analytical services (average satisfaction score 4.2 out of 5) over narrowly specialised solutions (3.4 out of 5). These results contrasted with the conclusions of I. Dobre *et al.* (2021), who justified the advantages of specialised platforms adapted to specific agricultural tasks, arguing that such platforms had a lower entry threshold for farmers lacking advanced digital skills. The empirical data obtained demonstrated a more complex picture: for the initial stage of digitalisation, narrowly specialised solutions were indeed more effective (27.4% higher likelihood of successful implementation), but for farms that had overcome the digital threshold, integrated platforms provided significantly higher long-term effectiveness.

The study results revealed the critical role of hybrid interaction models combining elements of online and offline communication in overcoming digitalisation barriers among small agricultural producers (implementation effectiveness was 34.2% higher compared to purely digital solutions). This complemented the findings of T. Soma and B. Nuckchady (2021), who emphasised the defining role of educational and demographic factors. Regression analysis confirmed the importance of both competency-based characteristics of farmers ($\beta = 0.39$, $p < 0.01$) and psychological factors, particularly trust in technology ($\beta = 0.61$, $p < 0.01$), which explained the high effectiveness of hybrid models that preserved elements of traditional personal interaction, creating psychological comfort for farmers during digital transformation. The study of the effectiveness of demand forecasting models based on artificial intelligence demonstrated substantial differences in perceived value between forecasting tools (average score 4.6 out of 5) and solutions for optimising current processes (3.8 out of 5). These results aligned with the studies of R. Dara *et al.* (2022), who highlighted the advantages of AI in analytical and predictive functions. The accuracy of the developed ensemble forecasting model (93.7%) was comparable to the indicators of the best global analogues, confirming the potential of advanced machine learning algorithms for use in the Kazakhstani agrarian market.

The research results revealed the need for state support in forming unified interoperability standards for agricultural digital platforms, which would reduce entry barriers for small farms by 34.7% and increase the efficiency of the digital ecosystem by 42.3%. These conclusions were in line with the discussion on the role of the state in the digital transformation of the agro-industrial complex (Kalambet *et al.*, 2016; Samoichuk *et al.*, 2016). The Digital Kazakhstan State Program (2018) justified the necessity of direct government intervention and centralised digitalisation planning, whereas I. Tomorri *et al.* (2025) demonstrated the advantages of market competition. Statistical analysis confirmed that the optimal model lay in state standardisation and the creation of infrastructural foundations, while maintaining market competition in the development of specific functional solutions. The study revealed a significant discrepancy between perceived and actual digitalisation barriers among small farming households: in subjective assessments, financial constraints dominated (79.2% of respondents cited financial constraints as critical), whereas objective data indicated the primacy of organisational and informational barriers ($r = 0.71$ with implementation delay at $p < 0.01$). These results contrasted with the study by O. Visser *et al.* (2021), which highlighted financial constraints as fundamental. Statistical analysis showed that with the presence of a minimal threshold level of funding (from 1.2 million tenge for basic digitalisation), further success in the process was predominantly determined by non-financial factors: organisational maturity ($\beta = 0.58$, $p < 0.01$), availability of informational support ($\beta = 0.47$, $p < 0.01$), and the level of trust in technological innovation ($\beta = 0.43$, $p < 0.01$).

The pilot implementation of the developed recommendations demonstrated substantial improvement in key economic indicators: the average volume of product sales increased by 31.6% ($p = 0.003$), the average sales margin rose by 33.0% ($p < 0.001$), and the share of unsold products decreased by 41.6% ($p = 0.001$). These indicators were comparable to the results of similar projects in Eastern European countries (26-29%) but were lower than those of developed countries (32-41%). The most significant breakthrough was achieved in the share of products sold through digital channels, which rose from 7.8% to 32.5% (an increase of 316.7%, $p < 0.001$), with an extremely high effect size (Cohen's $d = 2.32$), which aligned with the data on sales channel transformation under the influence of digitalisation, as presented in the study by G.M. Kalkabayeva *et al.* (2023). The results should also be considered in the context of the ethical aspects of artificial intelligence implementation. The data obtained on the high effectiveness of forecasting models (accuracy 93.7%) should be interpreted in light of the ethical principles formulated by R. Dara *et al.* (2022). The study showed that 68.4% of surveyed farmers expressed concern about the confidentiality of collected data, and 52.7% mentioned insufficient understanding of algorithmic operations as a factor undermining trust in technology.

Thus, the study offered a comprehensive solution to key debates surrounding the digital transformation of small farming households in Kazakhstan, demonstrating the nonlinear nature of the relationship between economic, organisational, and psychological factors in the implementation of digital platforms. The empirical data obtained confirmed the necessity of a differentiated approach to different categories of producers, taking into account the digital maturity, regional specificities, and organisational characteristics, and also pointed to the critical importance of hybrid implementation models combining technological innovations with traditional elements of interpersonal interaction.

CONCLUSIONS

As a result of the conducted study on the impact of digital platforms and artificial intelligence capabilities on product sales by small farming households in Kazakhstan, the following key scientific findings were obtained. It was established that the introduction of digital tools allowed an average increase in product sales volume by 31.6%, alongside an increase in sales margin by 33.0% and a reduction in the share of unsold products by 41.6%. Significant regional differences in the level of digitalisation were identified: the digital maturity index ranged from 0.38 in the North Kazakhstan region to 0.20 in the Kyzylorda region, due to both economic factors and the availability of digital infrastructure. A direct correlation between the level of digitalisation and farm profitability was proven: net profit increased from 12.8% in farms with a basic level to 27.3% in farms with an advanced level of digitalisation.

The most effective digital tools for different categories of farms were identified: for micro-farms, social networks and messengers were optimal (ROI 165-187%); for small farms – specialised marketplaces (ROI 194-218%); for medium farms – comprehensive solutions with analytical tools (ROI 227-256%). An ensemble demand forecasting model based on machine learning algorithms was developed and successfully tested, achieving an accuracy of 93.7%, comparable with the best international analogues. Key factors determining the successful implementation of digital tools were identified: readiness for change ($r = 0.67$), computer literacy ($r = 0.63$), and initial level of digitalisation ($r = 0.58$). It was established that excessive complexity of implemented solutions had a negative impact on economic outcomes ($\beta = -0.184$), confirming the need for phased implementation of digital tools in accordance with the digital maturity of the farm. Based on the results obtained, practical recommendations were developed, the implementation of which will help increase the efficiency of product sales by small farming households in Kazakhstan.

For small farming households, phased implementation of digital tools is recommended, taking into account specialisation and the current level of digital maturity. At the initial stage, it is optimal to use simple and intuitive solutions: creating business accounts on social networks and messengers, registration on specialised marketplaces. As experience accumulates and digital competences grow, it becomes appropriate to introduce more complex tools: integration with electronic payment systems, use of analytical services for demand forecasting. For state bodies managing the agricultural sector, it is recommended to develop differentiated digitalisation support programmes that reflect regional specificities. In regions with a low level of digital infrastructure, the priority is to establish a network of anchor digital hubs that provide access to high-speed internet and educational services. It is also advisable to introduce unified interoperability standards for agricultural digital platforms, which would reduce entry barriers for small farms by 34.7%. For developers of digital solutions, it is recommended to create adaptive platforms with modular structures that allow gradual expansion of functionality according to the growing needs of farming households. Particular attention should be paid to the development of intuitive interfaces and the provision of comprehensive technical support, including educational materials in Kazakh and Russian.

Prospects for further research are associated with in-depth study of the mechanisms for integrating small farming households into global digital ecosystems. In the short term, it is relevant to explore the adaptation possibilities of advanced digitalisation models of farming from the USA, the Netherlands, and Israel to the specific conditions of Kazakhstan. In the medium term, the development of cross-sectoral digital solutions uniting agricultural producers with representatives of the food industry, logistics, and retail is of interest. In the long term, it is necessary to investigate the potential of blockchain technologies to ensure transparency of supply chains and enhance consumer trust in the products of small farming households.

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Анотація. Метою дослідження була оцінка впливу цифрових платформ та технологій штучного інтелекту на ефективність збуту сільськогосподарської продукції малими фермерськими господарствами Казахстану порівняно з досвідом країн Центральної Азії та світовими практиками. Дослідження проводилося з березня 2023 року по лютий 2025 року в 14 областях Республіки Казахстан із застосуванням комплексної методології, що включає стратифіковану випадкову вибірку, структуровані інтерв'ю з керівниками 324 малих фермерських господарств (з чисельністю працівників до 10 осіб та річним оборотом не більше 30 млн теньге). платформ (AgroSmart.kz, Egistic, DigiField, QazFarm, AgroMap, Agroplatforma.kz, Agro.kz, Farm.kz). Проведено дисперсійний аналіз ANOVA, регресійний та кореляційний аналіз, а також застосовано методи машинного навчання (Random Forest, XGBoost) для розробки прогностичної моделі. Статистичний аналіз даних показав, що впровадження цифрових інструментів дозволило збільшити обсяги продажів у середньому на 27,3 % за скорочення витрат на посередників на 18,6 %. Найбільшу ефективність продемонстрували господарства, які використовують комбінацію локальних торгових платформ (AgroSmart.kz, Agro.kz) та спеціалізованих сервісів прогнозування попиту. Регіональний аналіз виявив суттєві відмінності в рівні цифровізації: у південних областях (Туркестанська, Жетисуська) 64,2 % фермерів регулярно використовували не менше двох цифрових каналів збуту, тоді як у північних (Костанайська, Північно-Казахстанська) цей показник становив лише 38,7 %. Розроблена з використанням алгоритмів машинного навчання прогностична модель продемонструвала точність передбачення сезонних коливань попиту 87,4 % під час тестування на історичних даних 2018-2023 років. Пілотне впровадження розроблених рекомендацій у діяльність 23 малих фермерських господарств дозволило досягти середнього зростання виручки на 31,5 % за скорочення часу на пошук покупців на 43,2 %. Дослідження довело економічну доцільність впровадження цифрових інструментів у практику малих фермерських господарств Казахстану навіть за обмеженого бюджету на цифровізацію

Ключові слова: малі фермерські господарства; агропромисловий комплекс; цифрові платформи; ефективність збуту; модель прогнозування попиту; Казахстан, машинне навчання