International Journal of Sustainable Development and Planning
Vol. 21, No. 9, September, 2026, pp. 4371-4384
Journal homepage: http://iieta.org/journals/ijsdp

# The Impact of Digital Technologies on the Economic and Social Sustainability of Rice Production

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https://doi.org/10.18280/ijsdp.210934

**Received:** 18 June 2026
**Revised:** 11 August 2026
**Accepted:** 21 August 2026
**Available online:** 30 September 2026

***Keywords:***
*digital technologies, rice production, agricultural digitalisation, sustainable agriculture, employment effects, agricultural productivity*

**ABSTRACT**

This study offers a thorough evaluation of the economic and social impacts of digital technologies in rice production. Although the digital transformation of agriculture has been extensively explored, empirical evidence specific to the rice sector and Central Asian context remains scarce. To fill this gap, a quantitative survey was carried out among employees of rice-producing enterprises in Kazakhstan's Kyzylorda region (N = 152). The data collected were analysed using reliability testing, non-parametric correlation methods, regression analysis, and the Kruskal–Wallis test. The findings demonstrate a complex and multi-faceted influence of digital technologies on rice production systems. The adoption of digital solutions shows a strong positive correlation with key economic metrics, such as crop yield, total harvest, and enterprise profitability. Conversely, the social effects of digitalisation are more ambiguous. The results suggest that digital technology adoption does not reduce physical workload and is linked to declines in employment. Additionally, statistically significant variations in digital adaptation were observed across different age groups, indicating the emergence of generational gaps in digital skills. Overall, the findings emphasise both the economic advantages and social challenges of digitalisation in agriculture, offering valuable insights for policymakers, farm managers, and researchers focusing on sustainable agricultural development.

## 1. INTRODUCTION

The digitalisation of agriculture has become a vital part of modern agrarian transformation, driven by the intersection of demographic, environmental, and economic challenges. According to projections by the United Nations, the global population is expected to continue increasing over the next 50–60 years and is forecast to peak at around 10.3 billion in the mid-2080s, up from 8.2 billion in 2024 [1]. This rapid population growth exerts considerable pressure on global food systems and will necessitate a significant boost in food production. Simultaneously, climate change is diminishing the productivity and dependability of agricultural systems. Recent assessment reports highlight the rising frequency of extreme weather events and regionally uneven declines in crop yields, both of which threaten food availability and the stability of supply chains [2]. Furthermore, structural labour challenges are becoming increasingly apparent in the agricultural sector. The ageing of rural populations and the outward flow of labour from agriculture have already been documented in OECD analyses and may restrict the sector's capacity to expand production through conventional methods. In this context, digitalisation presents opportunities to alleviate these constraints by boosting labour productivity and enabling greater automation [3]. As a result, digital technologies are progressively recognised by the Food and Agriculture Organization (FAO) as a key tool for improving agricultural productivity, reducing production losses, and enhancing the resilience of food systems, despite the sector remaining comparatively under-digitalised [4].

As one of the most vital branches of crop production, rice cultivation plays a central role in securing food security and socio-economic stability in many parts of the world [5]. Rice is the staple food for over half the global population and makes up a significant portion of caloric intake, accounting for up to 21% of daily dietary energy consumption [6]. As a result, rice remains one of the most strategically important agricultural commodities in the twenty-first century. Around 90% of global rice production and consumption are concentrated in Asian countries [7], where rice cultivation acts as both a fundamental food resource and a major source of employment and income for rural communities. Nonetheless, the significance of rice production extends beyond regional boundaries. The stability of rice output and trade greatly influences global food markets and price trends, especially considering the dominant role played by leading Asian producers and exporters [8]. In Central Asian nations, although production volumes are comparatively modest in

relation to Southeast Asia, rice cultivation still holds strategic importance for diversifying food sources, enhancing local food security, and supporting the sustainable development of agriculture. This is particularly relevant in countries where climatic and water resource conditions impose additional constraints on agricultural productivity [9]. These factors highlight the need for innovative solutions, including digital technologies, to improve the productivity, adaptability, and resilience of rice production systems amid complex environmental and socio-economic challenges.

Recent years have seen an increase in scholarly research exploring the influence of digital innovations on specific subsectors of agriculture. Several studies provide evidence of a consistent positive impact of adopting information and communication technologies (ICT) in cereal crop production [10]. Other research examines the digital transformation of greenhouse farming, emphasising the economic advantages of integrating agricultural activities with digital platforms [11]. Additional studies show the significant effect of ICT adoption on the production of chilli peppers in crop cultivation systems [12]. Simultaneously, a parallel stream of research has emerged that investigates digitalisation within the broader context of sustainable agricultural development. Scholars analyse the economic, environmental, and social impacts of the digital transformation of agriculture from this perspective. Economic outcomes are typically measured through indicators such as productivity [13, 14], total agricultural output and crop yields [10, 15], and farmers' participation in agricultural markets [16]. Environmental impacts are usually assessed in terms of reduced emissions and improved ecological efficiency of agricultural production [17-21]. Social outcomes are generally explored through changes in farmers' income levels [22-24], working conditions, and the quality of rural employment [25, 26].

Despite notable progress in understanding the role of digitalisation in enhancing agricultural efficiency, existing research remains largely fragmented. Most studies tend to focus either on specific indicators or on individual agricultural subsectors. Consequently, the number of studies specifically exploring the impact of digitalisation on rice production remains limited. Furthermore, there is a noticeable gap in empirical research conducted in the context of Central Asia [27]. Against this backdrop, the present study aims to offer a comprehensive assessment of the contribution of digital technologies to the economic and social sustainability of rice production. To achieve this goal, the study addresses the following tasks.

1) To formulate research hypotheses about the impact of digital technologies on the performance of rice-producing enterprises based on a systematic review of the existing literature.

2) To analyse the impact of digital technologies on production outcomes (rice yield and gross harvest), financial and economic outcomes (profitability), and social outcomes (changes in workforce size and increased internal competition among employees) within rice-producing companies.

3) To interpret the empirical findings in relation to existing academic research and to identify directions for future scholarly enquiry in this field.

4) To develop practical recommendations aimed at enhancing the effectiveness of implementing digital solutions in rice cultivation based on the study's findings.

## 2. LITERATURE REVIEW AND RESEARCH HYPOTHESES

The digital transformation of agriculture is increasingly recognised as a crucial factor in enhancing the efficiency of agricultural production. Digital solutions extend the capacity for monitoring production processes, improve access to information, and enable more efficient resource management [28]. Consequently, the adoption of digital technologies can positively influence crop yields and the overall performance of agricultural systems. In particular, precision agriculture technologies play a vital role in boosting production efficiency. These include remote sensing and satellite monitoring systems that enable farmers to more accurately assess crop conditions, soil moisture levels, and plant nutrient requirements, thereby facilitating more effective resource optimization [29]. Empirical evidence indicates that implementing such technologies can lead to stable production outcomes, even under adverse climatic conditions. In some cases, crop yields achieved through precision agriculture technologies significantly surpass regional averages [15]. Furthermore, the use of soil moisture sensors and digital irrigation monitoring systems contributes to higher crop productivity by optimising irrigation schedules and water management practices [30]. Beyond production technologies, digital information and communication platforms also play a crucial role by increasing farmers' access to market information and production resources. Reducing information asymmetries and transaction costs through digital services can improve agricultural productivity and the economic performance of farming enterprises [31]. However, empirical research shows that the effects of digital technology adoption are not always uniform. For instance, the introduction of mobile technologies may influence farmers' production decisions, such as encouraging crop diversification, but does not necessarily lead to statistically significant increases in overall production volumes [32]. Based on the theoretical considerations and empirical findings discussed above, the following research hypothesis is formulated:

**H1:** The adoption of digital technologies boosts perceived crop yield and total harvest volumes in rice-producing enterprises.

A review of the scientific literature shows that evaluating the effectiveness of agricultural digitalisation should go beyond just crop yield and production figures. The long-term sustainability of adopting digital technology mainly relies on its effect on the economic performance of farming businesses, especially regarding income levels and farm profitability. Existing studies indicate that digital transformation's impact on farmers' incomes operates through several interconnected channels, including increased production efficiency, better product quality, and structural shifts within the agricultural economy [22]. The growing use of digital platforms and services enhances farmers' access to information about resources, financial tools, and market options. By reducing information asymmetries and transaction costs, these technologies strengthen interactions between farmers, suppliers, and buyers of agricultural goods. Consequently, digital technologies generate additional economic opportunities that can boost income for rural households [23]. Empirical evidence also shows that expanding digital infrastructure, especially broadband internet and mobile connectivity, produces measurable economic benefits for rural populations. For instance, a 1% increase in broadband

coverage may lead to about a 0.11% rise in farmers' incomes, while a 1% increase in mobile phone use could raise income levels by roughly 0.07%. Simultaneously, these improvements are linked to an estimated 0.14% growth in agricultural output [33]. These findings underscore that digital connectivity in rural areas is an important factor driving the economic performance of agricultural production.

Nevertheless, the economic outcomes of digital technology adoption remain varied. High initial investment costs, the need for equipment upgrades, and uncertainty about the return on investment may hinder the spread of precision agriculture technologies, especially among small-scale farms where perceived investment risks are higher [34]. Sometimes, positive economic effects only become apparent when farms have modernised equipment or when digital technologies are introduced through service-based models. This highlights that the income benefits of digitalisation largely depend on the current level of technological capacity within agricultural enterprises. Overall, existing research suggests a positive link between the digitalisation of agriculture and increased farm income, although the extent and stability of this effect are heavily influenced by institutional, infrastructural, and resource-related factors that affect the adoption of digital technologies. Based on these points, the following hypothesis is proposed:

**H2:** The utilisation of digital technologies enhances the perceived profitability of rice-producing enterprises.

The assessment of how digital technologies affect the performance of agricultural enterprises should not be limited solely to economic indicators. Although it is often recognised that even farmers adopting socially and environmentally focused farming models tend to prioritise economic outcomes in their decision-making processes [35], the social effects of digitalisation have gained increasing importance in current research on the sustainability of the agricultural sector. A substantial body of literature investigates the social impacts of digital technology adoption, particularly its effect on working conditions and farmers' daily activities. Empirical evidence indicates that using digital tools may be linked to improvements in farmers' health and greater resilience to stress-related factors. For instance, farmers who utilise digital solutions often show better health outcomes and lower vulnerability to economic and production shocks [23]. Several studies also suggest that digital technologies can lessen physical workload and enhance the flexibility of work organisation within agricultural enterprises [36]. At the same time, empirical findings are mixed. In some cases, adopting digital solutions does not result in significant changes in working hours or leisure time, and the perceived effects vary considerably depending on the types of technologies employed and the characteristics of the farms involved [37].

Similarly, studies examining the working conditions of small-scale farmers indicate that the implementation of digital agricultural technologies may help reduce heavy physical labour and simplify certain production processes. However, empirical evidence also points to the emergence of new organisational and operational challenges associated with expanding farm activities, longer working hours, and increased labour intensity, highlighting the complex and sometimes contradictory social effects of digitalisation [25]. Another possible result of digitalisation is the transformation of labour procedures. The use of digital monitoring and performance analysis systems may enhance oversight of work activities and potentially intensify labour processes, especially in contexts involving hired labour [26]. Therefore, the impact of digital technologies on the social aspects of agricultural enterprises is influenced not only by the level of technological adoption but also by the institutional setting in which these technologies are implemented, as well as by the employment structure and the organisational management of farms. Despite variations in empirical findings, the overall body of research suggests that applying digital technologies in agricultural production generally helps reduce physical workload and brings about changes in working conditions within the sector. Based on these arguments, the following hypothesis is formulated:

**H3:** The adoption of digital technologies in agricultural production helps to lessen the perceived physical workload of employees.

Another significant social impact of digitalisation, which may potentially have negative consequences, is the restructuring of employment patterns linked to the automation of production processes and the declining demand for manual labour. Several studies indicate that the optimisation of production operations and the expanding use of digital technologies could lead to a reduction in demand for hired labour. For instance, research by Miine et al. [25] shows that the adoption of digital agricultural technologies in Ghana was accompanied by a decrease in the number of hired workers due to better access to agronomic information and increased farm technological capacity. This transformation of the production process was reflected in a gradual shift from labour-intensive methods towards more capital-intensive technologies, the expanded use of agricultural machinery, and the consolidation of farms, all of which contributed to lowering labour demand. Simultaneously, new forms of cooperation among farmers emerged, based on mutual assistance and shared resource use, which also affected the redistribution of labour flows within rural areas.

Similar trends have been observed in other countries, such as China, where ongoing processes of mechanisation and automation are gradually replacing certain types of traditional agricultural employment, despite the continued importance of the agricultural sector as a source of employment for rural populations [38]. Studies addressing the broader effects of automation further demonstrate that technological change tends to impact occupations involving routine tasks the most. According to estimates by Frey and Osborne [39], approximately 47% of jobs in the United States are potentially at high risk of automation in the long term, particularly in sectors such as transportation, logistics, administrative work, and manufacturing. However, subsequent research suggests that automation is more likely to substitute specific tasks rather than entire occupations, meaning that the actual scale of job displacement may be considerably lower [40].

Although some scholars are somewhat optimistic that digital technologies might transform current jobs and create new employment opportunities, a considerable part of the academic literature expresses concerns about the possible increase in unemployment resulting from the expansion of digital technologies in the agricultural sector. Based on these arguments, the following hypothesis is proposed:

**H4:** The adoption of digital technologies results in a decrease in perceived employment within rice-producing enterprises.

The effects of digitalisation discussed above demonstrate its multifaceted influence on production and labour processes within agricultural enterprises. Another important dimension

of analysis concerns the impact of digital technologies on the transformation of the human capital structure within the agricultural sector. Early studies on digital inequality suggested that the level of digital skills is largely determined by users' demographic characteristics, particularly age and gender, while formal education tends to exert a less pronounced influence. Instead, practical experience with technology and the motivation to use digital tools appear to play a decisive role in shaping digital competencies [41]. More recent empirical studies confirm that younger workers generally adapt more rapidly to the introduction of digital solutions, whereas the likelihood of actively using digital technologies tends to decrease as farmers' age increases [23]. Comparative international research on digital inequality further demonstrates that age remains one of the most persistent factors differentiating users in terms of their level of information technology usage [42]. In particular, older age groups are characterised by a higher proportion of individuals who completely refrain from using the internet, while among younger users the level of engagement with digital technologies is significantly more widespread and consistent.

Building on this line of research, recent studies have increasingly examined the social implications of disparities in digital skills. Scholars observe that the adoption of digital technologies may amplify intergenerational differences in the labour market, as workers' ability to effectively use digital tools becomes an important factor for professional competitiveness. Consequently, younger employees with higher levels of digital literacy may enjoy additional advantages in employment opportunities and career progression. Conversely, older workers may face a greater risk of professional marginalisation amid ongoing technological change [26, 37]. Based on these arguments, the following hypothesis is proposed:

**H5:** There are statistically significant differences between age groups of workers in their perceived ability and readiness to use, learn, and adapt to digital technologies.

## 3. METHOD

This study employs a quantitative research design based on a survey administered to a purposive sample of representatives from rice-producing enterprises in Kazakhstan, with a particular focus on the Kyzylorda region. The selection of this region was deliberate. Existing studies suggest that rice consumption in Central Asia totals approximately one million metric tonnes annually, with Uzbekistan leading consumption (around 500,000 tonnes), followed by Kazakhstan (about 350,000 tonnes). The total volume of rice production in the region is also close to one million tonnes, with the largest shares produced in Uzbekistan (341,000 tonnes) and Kazakhstan (431,000 tonnes) [9]. In Kazakhstan, rice cultivation is concentrated in four regions: Almaty, Zhetysu, Zhambyl, and Kyzylorda. However, the Kyzylorda region accounts for roughly 98% of national rice production [43]. For this reason, respondents were selected from rice-growing enterprises located in this region, including general partnerships, limited liability partnerships (LLPs), and peasant farms.

The survey was conducted between September and October 2025 among employees of five rice-producing enterprises in Kazakhstan's Kyzylorda region.

Sample and recruitment. The survey included 152 respondents from five rice-producing enterprises in Kyzylorda Region, Kazakhstan. Respondents represented three organisational forms: 66 (43.4%) from full partnerships, 78 (51.3%) from LLPs, and 8 (5.3%) from peasant farms. Participants were recruited through direct contact by the researchers and with the assistance of the managers of the participating enterprises. The survey was conducted among employees with direct experience of agricultural production and the use of digital technologies in their work. The exact number of respondents contributed by each enterprise was not systematically recorded during data collection; therefore, an enterprise-level response rate and a precise distribution of respondents across the five enterprises could not be reliably calculated.

Participants represented various occupational positions within these enterprises, ranging from operational workers to managers at different organisational levels (see Table 1).

**Table 1.** Demographic characteristics of the participants in the study

| Indicator | Category | Frequency N | Percentage (%) |
|---|---|---|---|
| Age | 20–25 years | 39 | 25.7 |
| | 26–35 years | 60 | 39.5 |
| | 36–45 years | 28 | 18.4 |
| | 46–55 years | 20 | 13.2 |
| | 56–65 years | 5 | 3.3 |
| Gender | Male | 130 | 85.5 |
| | Female | 22 | 14.5 |
| Education level | Secondary education | 51 | 33.6 |
| | Higher education | 95 | 62.5 |
| | Postgraduate education (Master's degree) | 6 | 3.9 |
| Work experience in agriculture | Up to 5 years | 48 | 31.6 |
| | 5–10 years | 55 | 36.2 |
| | 11–20 years | 38 | 25.0 |
| | 21–25 years | 5 | 3.3 |
| | More than 25 years | 6 | 3.9 |
| Occupation | Agronomist | 9 | 5.9 |
| | Engineer | 7 | 4.6 |
| | Technologist | 17 | 11.2 |
| | Worker | 90 | 59.2 |
| | Accountant | 1 | 0.7 |
| | Economist | 3 | 2.0 |
| | Marketing specialist | 4 | 2.6 |
| | Middle-level manager | 17 | 11.2 |
| | Senior manager | 4 | 2.6 |

Note: Percentages are calculated based on valid responses. Total sample size: N = 152.

The demographic characteristics of the study participants are shown in Table 1. In the sample, the largest proportion of respondents falls within the 26–35 age group (39.5%), followed by those aged 20–25 years (25.7%). Together, these groups highlight the dominance of young, economically active workers in the surveyed population, accounting for 65.2% of respondents. Participants aged 36–45 years make up 18.4% of the sample, while older age groups are less represented. The gender makeup of the sample is characterised by a significant predominance of male respondents (85.5%), with female respondents comprising 14.5%, reflecting the typical gender composition of the agricultural sector. In terms of education,

the majority of respondents hold higher education degrees (62.5%), while 33.6% have secondary education, and 3.9% possess postgraduate qualifications at master's level. Regarding work experience in agriculture, 31.6% of respondents report up to five years, 36.2% between five and ten years, and 25.0% between eleven and twenty years. A smaller portion reported longer experience, with 3.3% indicating 21–25 years and 3.9% more than 25 years in the agricultural sector. The professional structure shows that the largest group comprises operational workers (59.2%), followed by technologists (11.2%) and middle-level managers (11.2%), while other professional categories, including agronomists, engineers, accountants, economists, marketing specialists, and senior managers, make up smaller proportions of the sample.

The primary research instrument used in this study was a structured questionnaire developed based on a review of relevant academic literature on the digitalisation of agriculture and its socio-economic impacts. The questionnaire was adapted from the survey instrument proposed by Luque-Reyes et al. [44], with modifications made to reflect the institutional and socio-economic characteristics of the national agricultural sector. In particular, several sections of the questionnaire were revised, especially those relating to the perception and practical use of digital technologies. The wording of the questions was clarified and reformulated, and additional variables were added to ensure that the instrument aligned closely with the objectives of this study.

The questionnaire comprised five sections that collectively explore the key aspects of digital transformation in rice production. The first section focused on demographic characteristics and the overall profile of the farms represented by the respondents. The second section scrutinised the usage and frequency of digital and precision technologies in rice cultivation. The third section evaluated the economic, social, and environmental impacts associated with adopting digital technologies. The fourth section investigated respondents' perceptions of digital technologies, including issues such as the perceived difficulty of adopting innovations, the compatibility of new technologies with traditional agricultural practices, and the level of trust in decisions supported by AI. The final section examined the extent of institutional support for the implementation and dissemination of digital technologies, including assistance provided by government and local authorities. Collectively, these sections were designed to address the primary aim of the study, which is to assess the influence of digital technologies on the social and economic dimensions of sustainability among rice-producing enterprises. It is important to clarify that yield, gross harvest, profitability, and workforce reduction were treated as perceived outcomes rather than objective enterprise-level indicators. Respondents were asked to assess, based on their experience and observations, whether the use of digital technologies had affected these outcomes. Accordingly, the corresponding variables represent employees' perceptions of changes in production, economic performance, and workforce requirements, as measured by the questionnaire's Likert-scale responses. These measures should not be interpreted as direct observations of actual yield, accounting profitability, gross output, or changes in employment. Accordingly, the regression results concerning these variables are interpreted as associations between digital technology adoption and perceived outcomes rather than as evidence of objectively measured changes at the enterprise level.

The collected survey data were processed and analysed using IBM SPSS Statistics (version 29.0.2.0). The statistical analysis included reliability testing with Cronbach's alpha to evaluate the internal consistency of the measurement scales. Normality tests for the distribution of variables were conducted using the Kolmogorov–Smirnov and Shapiro–Wilk tests. Due to the distributional characteristics of the data, non-parametric analysis was employed using the Kruskal–Wallis test. Additionally, Spearman's rank correlation coefficient (R) was used to examine relationships between variables, and regression analysis was performed to assess the impact of digital technologies on the performance indicators of rice-producing enterprises.

To evaluate the internal consistency of the measurement scales, a reliability analysis was performed using Cronbach's alpha coefficient (Table 2).

**Table 2.** Reliability statistics

| Indicator | Cronbach's Alpha | N of Items |
|---|---|---|
| Digital Technologies | 0.879 | 8 (8-15) |
| Yield and Harvest | 0.877 | 3 (16, 17, 21) |
| Profit | 0.876 | 3 (18-20) |
| Physical Activity | 0.810 | 5 (22-23, 33, 34, 37) |
| Workforce Reduction | 0.812 | 4 (25, 27, 28, 29) |
| Adaptation to Digitalisation | 0.776 | 5 (24, 26, 31, 32, 36) |

The survey instrument comprised 41 items organised into five sections covering demographic and farm characteristics (Items 1–7), the use of digital and precision technologies (Items 8–15), the economic, social and environmental effects of digital technologies (Items 16–25), perceptions and adoption of digital technologies (Items 26–32), and institutional support for digitalisation (Items 33–41). The full English version of the questionnaire is provided in the Supplementary Materials.

The questionnaire was adapted from the survey instrument developed by Luque-Reyes et al. [44] to assess agri-food digitalisation, with selected items modified to reflect the context of rice-producing enterprises in Kazakhstan. The adaptation preserved the original conceptual meaning of the items while modifying their wording where necessary to reflect the specific research context. The sources of the adapted questionnaire items and the main wording modifications are summarised in Table A1. Initially, the questionnaire was developed in Kazakh based on the instrument developed by Luque-Reyes et al. [44]. Subsequently, it was translated into Russian and English using the forward-backward translation method: an independent bilingual translator carried out the initial translation, which was then translated back into Kazakh by a second translator who was not familiar with the original text. The research team analysed and resolved discrepancies between the original text and its back translation. The Kazakh and Russian versions were checked for semantic equivalence by a bilingual reviewer before publication.

The questionnaire was reviewed by three members of the Department of Economics and Management at a regional university who hold Science degrees and have research experience in agriculture. They assessed the wording, relevance, and alignment of the questions with the study context before the main survey and made clarifications to the

questionnaire.

Attitudinal items were measured on a five-point Likert-type scale from 1 (strongly disagree) to 5 (strongly agree), while frequency-based items were measured on a five-point scale from 1 (never) to 5 (always). The complete questionnaire, including the response options, is provided in the Supplementary Materials.

The composite indicators used in hypothesis testing were specified *a priori* in line with the study's theoretical framework. For each construct, a composite score was calculated as the arithmetic mean of the corresponding questionnaire items. The revised measurement table reports the specific questionnaire items included in each construct, the number of items, and the corresponding Cronbach's alpha coefficient.

Internal consistency was assessed separately for each theoretically specified construct using Cronbach's alpha. Coefficients ranged from 0.776 to 0.879, indicating satisfactory to high internal consistency across the study indices. The specific item composition of each index is reported in Table 2 to ensure transparency in the index construction process.

**Table 3.** Normality tests for the study variables

| Variable | Kolmogorov-Smirnov[a] | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|
| | Statistic | df | Sig. | Statistic | df | Sig. |
| Yield and Harvest | 0.441 | 152 | < 0.001 | 0.553 | 152 | < 0.001 |
| Profit | 0.445 | 152 | < 0.001 | 0.573 | 152 | < 0.001 |
| Physical Activity | 0.304 | 152 | < 0.001 | 0.706 | 152 | < 0.001 |
| Workforce Reduction | 0.353 | 152 | < 0.001 | 0.727 | 152 | < 0.001 |
| Adaptation to Digitalisation | 0.244 | 152 | < 0.001 | 0.850 | 152 | < 0.002 |

The distributional properties of the study variables were assessed using the Kolmogorov–Smirnov and Shapiro–Wilk tests (Table 3). Both tests indicated statistically significant deviations from normality in the observed variables. These results informed the choice of Spearman's rank R for the bivariate correlation analysis, as it does not require the variables to be normally distributed. However, non-normality of the observed variables was not, by itself, a reason to exclude ordinary least-squares (OLS) regression. OLS regression was used as a complementary analysis to estimate the linear association between the level of digital technology adoption and the study outcomes. The regression models report the R, coefficient of determination ($R^2$), adjusted $R^2$, unstandardised and standardised regression coefficients (B and β), t-statistics, F-statistics, and model significance. The results were interpreted as statistical associations rather than causal effects.

**Assessment of common-method bias.** Because the independent and dependent variables were collected from the same respondents via a single questionnaire at the same time, the potential for common-method bias was considered. Harman's single-factor test was conducted using principal component analysis with an unrotated one-factor solution. The analysis included the 34 substantive Likert-scale items measuring digital technology use, perceived economic, production, environmental and social outcomes, adaptation, and institutional conditions. The first unrotated component accounted for 48.20% of the total variance, below the conventional 50% threshold [45]. Thus, the analysis did not indicate that a single common factor accounted for the majority of the variance. Nevertheless, given the cross-sectional and self-reported nature of the data, residual common-method bias cannot be completely ruled out.

Ethical approval for the study was granted by the Ethics Committee of Korkyt Ata Kyzylorda University under Application No. 4301. The approval took effect on 1 September 2025 and remains valid until 30 June 2027.

**Informed consent statement.** Before completing the questionnaire, participants were informed of the study's purpose, the approximate duration of the survey (20 minutes), the voluntary nature of participation, and the anonymous presentation of the survey results. Participants were also provided with the researcher's contact information for any questions about the study. Participation was based on participants' confirmation that they had read the survey conditions and agreed to participate.

**Survey period.** The survey was conducted from September to October 2025 among employees of five rice-producing enterprises in the Kyzylorda Region of Kazakhstan. A total of 152 valid responses were obtained.

## 4. RESULTS

To test the hypotheses regarding the relationship between the level of digital technology adoption and the sustainability indicators of rice-producing enterprises, the study employed a sequential analytical approach combining Spearman's rank correlation analysis and regression analysis. This method enabled the evaluation of both the existence and direction of relationships, as well as the magnitude of their quantitative effects. The use of Spearman's R was justified because the analysed variables do not follow a normal distribution. Unlike parametric methods, Spearman's coefficient is robust against violations of the normality assumption and is widely used in empirical research to test hypotheses about monotonic relationships between variables. The analysis was conducted on a sample of 152 observations. In all regression models, the level of digital technology adoption served as the independent variable. Depending on the hypothesis under examination, the dependent variables included crop yield and total harvest volume, profit, physical workload, workforce reduction, and adaptation to digitalisation. The results of all regression models indicate a high explanatory power of the estimated specifications. Across all models, the effect of digital technologies remains consistent and statistically significant (Tables 4-7). The standardised regression coefficients are roughly $\beta \approx 0.70$, reflecting a substantial effect size. The high values of the t-statistics and significance levels ($p < 0.001$) affirm the reliability of the estimated coefficients, while the F-statistics demonstrate the overall statistical significance of the regression models. These findings enable the null hypothesis of no relationship between the analysed variables to be rejected at the 1% level of significance. In all models, the multiple correlation coefficient ($R \approx 0.70$) indicates a strong relationship between the level of digital technology adoption and the outcome variables. Furthermore, the values of the

adjusted coefficient of determination (Adjusted $R^2$) further support the robustness and reliability of the estimated models. Hypothesis 1 posits that the adoption of digital technologies results in increased perceived crop yield and total harvest volume in rice-producing enterprises.

**H1:** The adoption of digital technologies boosts perceived crop yield and total harvest volumes in rice-producing enterprises.

The correlation analysis revealed a strong, statistically significant positive association between digital technology adoption and employees' perceived crop yield and total harvest outcomes ($\rho = 0.639$, $p < 0.001$) (Table 4). These findings indicate that higher levels of digital technology adoption are associated with more favourable perceived outcomes in terms of crop yield and total harvest volume among rice-producing enterprises.

To further test Hypothesis 1 and quantitatively evaluate the effect of digital technologies on production efficiency, a regression analysis was carried out (Table 4). The coefficient of determination ($R^2 = 0.504$) demonstrates that 50.4% of the variation in perceived crop yield and total harvest volume can be explained by changes in the level of digital technology adoption. The estimated unstandardised regression coefficient for the variable "digital technologies" was $B = 0.795$ ($p < 0.001$). This indicates that a one-unit increase in the level of digital technology adoption results, on average, in a 0.795-unit rise in perceived crop yield and total harvest volume. Therefore, the results indicate a statistically significant and practically meaningful association between digital technology adoption and employees' perceived production performance outcomes. Conclusion for Hypothesis 1: The regression results were consistent with the correlation findings and provided support for a statistically significant positive association between employees' perceived production outcomes and the level of digital technology adoption in rice-producing enterprises.

**H2:** The utilisation of digital technologies enhances the perceived profitability of rice-producing enterprises.

The results of the correlation analysis (Table 5) demonstrate a strong and statistically significant positive relationship between the level of digital technology adoption and the perceived profitability of agricultural enterprises ($\rho = 0.668$, $p < 0.001$). These findings indicate that higher levels of digital technology adoption are associated with more favourable perceived financial outcomes in rice-producing enterprises.

To further examine Hypothesis 2, a regression analysis was performed (Table 5). The coefficient of determination ($R^2 = 0.508$) shows that 50.8% of the variation in profit can be attributed to changes in the level of digital technology adoption. The estimated unstandardised regression coefficient for the variable "digital technologies" was $B = 0.853$ ($p < 0.001$). This indicates that a one-unit increase in the level of digital technology adoption generally results in an increase of 0.853 units in the perceived profit of agricultural enterprises. Accordingly, the impact of digital technologies on profitability is both statistically significant and economically meaningful.

The regression results were consistent with the correlation findings and indicated a statistically significant positive association between digital technology adoption and employees' perceived financial performance of rice-producing enterprises. Conclusion for Hypothesis 2. Based on the correlation and regression results, Hypothesis 2 is supported, indicating a statistically significant positive association between the level of digital technology adoption and employees' perceived profitability outcomes in rice-producing enterprises.

**H3:** The adoption of digital technologies in agricultural production helps to lessen the perceived physical workload of employees.

The correlation analysis (Table 6) yielded a Spearman's rank R of $\rho = 0.683$ ($p < 0.001$). This result signifies a strong and statistically significant positive relationship between the level of digital technology adoption and the indicator of employees' perceived physical workload. The positive value of the R indicates that as digitalisation increases, the perceived physical workload variable also tends to increase. Since higher values of the physical workload variable correspond to greater physical exertion, the results suggest not a reduction in workload but rather an increase in perceived physical workload or a lack of the expected compensatory effect of digitalisation. Therefore, even though a statistically significant relationship exists between the level of digital technology adoption and employees' perceived physical workload, its direction contradicts the theoretical expectation outlined in Hypothesis 3.

To further test Hypothesis 3, a regression analysis was performed (Table 6). The coefficient of determination ($R^2 = 0.497$) shows that 49.7% of the variation in employees' perceived physical workload can be explained by changes in digitalisation levels. The estimated unstandardised regression coefficient for the variable "digital technologies" was $B = 0.693$ ($p < 0.001$). This indicates that a one-unit increase in digital technology adoption typically results in an increase of 0.693 units in employees' perceived physical workload. Therefore, the effect is positive and statistically significant.

**Table 4.** Correlation and regression analysis between the level of digital technology adoption, crop yield, and total rice harvest

| Variables | Spearman's ρ | *p*-Value | R | $R^2$ | Adj. $R^2$ | B | β | t | F | p (Model) |
|---|---|---|---|---|---|---|---|---|---|---|
| Digital technologies (independent) → Crop yield, gross harvest (dependent) | 0.639** | < 0.001 | 0.710 | 0.504 | 0.501 | 0.795 | 0.710 | 12.34 | 152.3 | < 0.001 |

Note: **. Correlation is significant at the 0.01 level (two-tailed).

**Table 5.** Correlation and regression analysis of digital technology adoption levels and profit

| Variables | Spearman's ρ | *p*-Value | R | $R^2$ | Adj. $R^2$ | B | β | t | F | p (Model) |
|---|---|---|---|---|---|---|---|---|---|---|
| Digital technologies (independent) → Profit (dependent) | 0.668** | < 0.001 | 0.713 | 0.508 | 0.505 | 0.853 | 0.713 | 12.45 | 154.92 | < 0.001 |

Note: **. Correlation is significant at the 0.01 level (two-tailed).

**Table 6.** Correlation and regression analysis between digital technology adoption levels and physical workload

| Variables | Spearman's ρ | *p*-Value | R | $R^2$ | Adj. $R^2$ | B | β | T | F | p (Model) |
|---|---|---|---|---|---|---|---|---|---|---|
| Digital technologies (independent) → Physical workload (dependent) | 0.683** | < 0.001 | 0.705 | 0.497 | 0.494 | 0.693 | 0.705 | 12.18 | 148.38 | < 0.001 |

Note: **. Correlation is significant at the 0.01 level (two-tailed).

**Table 7.** Correlation and regression analysis of the level of digital technology adoption and workforce reduction

| Variables | Spearman's ρ | *p*-Value | R | $R^2$ | Adj. $R^2$ | B | β | T | F | p (Model) |
|---|---|---|---|---|---|---|---|---|---|---|
| Digital technologies (independent)→ Workforce (staff) reduction (dependent) | 0.703** | < 0.001 | 0.695 | 0.484 | 0.480 | 0.696 | 0.695 | 11.85 | 140.46 | < 0.001 |

Note: **. Correlation is significant at the 0.01 level (two-tailed).

The regression outcomes agree with the correlation analysis and confirm that digital technology adoption does not decrease employees' perceived physical workload.

Conclusion for Hypothesis 3. Based on the correlation and regression results, Hypothesis 3 is not supported: higher levels of digital technology adoption were associated with higher perceived physical workload among employees, contrary to the hypothesised direction.

**H4:** The adoption of digital technologies results in a decrease in perceived employment within rice-producing enterprises.

The results of the correlation analysis ($\rho = 0.703$, $p < 0.001$) indicate a strong and statistically significant positive relationship between the level of digital technology adoption and perceived workforce reduction (Table 7). The positive sign of the R suggests that as digitalisation increases, the workforce reduction variable also rises, indicating a decreasing demand for labour resources in rice-producing enterprises. The positive correlation indicates that higher levels of digital technology adoption are associated with greater perceived workforce reductions in rice-producing enterprises. To further test Hypothesis 4, a regression analysis was conducted (Table 7). The coefficient of determination ($R^2 = 0.484$) shows that 48.4% of the variation in perceived workforce reduction can be explained by changes in digital technology adoption. The estimated unstandardised regression coefficient for the variable "digital technologies" was $B = 0.696$ ($p < 0.001$). This implies that a one-unit increase in digitalisation leads, on average, to an increase of 0.696 units in the perceived workforce reduction indicator. Therefore, the results indicate a statistically significant positive association between digital technology adoption and employees' perceived workforce reduction. The regression results were consistent with the correlation analysis.

Conclusion for Hypothesis 4. Based on the correlation and regression results, Hypothesis 4 is supported, as higher levels of digital technology adoption were associated with greater perceived workforce reduction in rice-producing enterprises.

**H5:** There are statistically significant differences between age groups of workers in their perceived ability and readiness to use, learn, and adapt to digital technologies.

For Hypothesis 5, an integrated composite indicator was constructed from five questionnaire items (Questions 24, 26, 31, 32 and 36). These items capture employees' ability and readiness to use, learn and adapt to digital technologies. The composite H5 indicator (Kruskal_H5) was calculated as the mean of the five items. Differences in the H5 indicator across age groups were examined using the Kruskal–Wallis test. Following the overall test, Bonferroni-adjusted pairwise comparisons were performed to identify potential differences between specific age groups. The effect size was assessed using epsilon-squared ($\varepsilon^2$).

The Kruskal–Wallis test (Table 8) revealed statistically significant differences in the H5 composite indicator across the five age groups ($H = 11.848$, $df = 4$, $p = 0.019$). The effect size was $\varepsilon^2 = 0.053$, indicating a modest overall effect.

Bonferroni-adjusted pairwise comparisons, however, did not identify statistically significant differences between any specific pair of age groups. The adjusted p-values ranged from 0.062 to 1.000, with the closest comparisons observed between age groups 3 and 1 (adjusted $p = 0.062$) and 4 and 1 (adjusted $p = 0.086$).

Overall, the findings suggest age-related variation in employees' perceived ability and readiness to use, learn, and adapt to digital technologies. However, the absence of statistically significant pairwise differences after Bonferroni adjustment indicates that these differences should be interpreted as an overall age-group pattern rather than as evidence of significant differences between specific age groups.

**Table 8.** Results of the Kruskal–Wallis test

| Ranks | | | |
|---|---|---|---|
| | **Age** | **N** | **Mean Rank** |
| Kruskal | 20–25 years | 39 | 95.62 |
| | 26–35 years | 60 | 74.88 |
| | 36–45 years | 28 | 65.91 |
| | 46–55 years | 20 | 63.95 |
| | 56–65 years | 5 | 56.30 |
| | **Total** | **152** | |

| Test Statistics[a,b] | |
|---|---|
| | Kruskal |
| Kruskal–Wallis H | 11,848 |
| df | 4 |
| Asymp. Sig. | 0.019 |

a. Kruskal Wallis Test b. Grouping Variable: 1. Age.

Since the grouping variable (age) is categorical and the dependent variable does not follow a normal distribution, the Kruskal–Wallis test was employed to test Hypothesis 5, which investigates differences in the level of digital technology adoption across age groups. The test results indicate statistically significant differences between age groups ($H = 11.848$; $df = 4$; $p = 0.019$). An examination of the mean ranks reveals that the highest values of the digital competence index are found in the youngest age group (20–25 years). Meanwhile, as respondents' age increases, there is a consistent

decline in the level of digital adaptation. The lowest values of the indicator were recorded among the older age cohorts. Therefore, Hypothesis 5, which suggests that statistically significant differences exist between age groups in the level of social and professional adaptation to digitalisation, is supported.

## 5. DISCUSSION

The present study broadens understanding of the role of digital technologies in agriculture by demonstrating their varied effects on key performance indicators of rice-growing enterprises. The results support Hypothesis 1 and suggest that adopting digital technologies is associated with higher perceived yields and greater gross rice production. This aligns with previous research [15, 31], which finds a positive link between adopting digital technology and agricultural productivity. A possible reason is more efficient resource use through crop monitoring systems, better assessment of water and nutrient needs [29], and maintenance of optimal soil moisture levels within the plant root zone [30], all achievable with digital technologies. However, empirical evidence is not always consistent. In particular, the spread of mobile technologies may alter farmers' production strategies, such as crop diversification, but these changes do not always yield statistically significant increases in output [32]. This implies that the effects of digitalisation might depend on various institutional, technological, and organisational factors.

Hypothesis 2 was also supported, indicating a positive impact of digital technology adoption on the perceived profitability of rice-growing enterprises.

This finding aligns with previous studies [22, 33, 34], which show that the digital transformation of agriculture helps to increase farmers' incomes. According to Addison et al. [23], this effect is mainly due to reduced transaction costs resulting from improved access to information, resources, and services necessary for agricultural production and marketing. At the same time, prior research suggests that positive financial outcomes often occur only when farms have suitable technological infrastructure or when digital solutions are implemented through service-based or platform-based models [34]. This indicates that the profitability of digital transformation largely depends on the initial level of technological capacity of farms and their ability to incorporate new technologies into existing production systems.

Contrary to initial expectations, Hypothesis 3, which proposed a decrease in perceived physical workload due to the adoption of digital technologies, was not supported.

One possible explanation is that digital technologies are often used to enhance monitoring and control over labour processes, which can result in increased labour intensity within organisations [26]. The academic literature offers mixed findings on this subject. Some studies report a reduction in physical workload and greater labour flexibility linked to digitalisation [36], while others suggest either no such effects or only partial implementations [25, 37].

Hypothesis 4, which suggested that a higher level of adoption of digital technologies would be associated with higher perceived levels of workforce reduction in rice-producing enterprises, was also supported.

The results align with the findings of Miine et al. [25] and Barki and Rachmah [38], who concluded that implementing digital technologies contributes to a decline in agricultural employment. One possible explanation for this is the substitution of human labour with machinery [38], as well as the high risk of computerisation in production-related roles, including those within the agricultural sector [39]. Simultaneously, previous studies highlight that automation generally affects specific tasks rather than entire occupations [39], suggesting that digitalisation may not only cause job reductions but also transform the structure of employment.

Hypothesis 5, which proposed statistically significant differences across age groups in employees' perceived ability and readiness to use, learn, and adapt to digital technologies, was supported by the overall Kruskal–Wallis test.

The results of the Kruskal–Wallis test ($H = 11.848$; $df = 4$; $p = 0.019$) showed variability in employees' adaptation to digital tools, which might contribute to workforce fragmentation and growing tensions between older and younger, more digitally adapted groups. These findings support previous research indicating that the use of digital technologies is heavily influenced by age [23, 41] and leads to a generational digital divide [26]. One possible reason is that older cohorts tend to lag behind younger groups in both the extent and frequency of internet use [42]. Consequently, some older workers may become increasingly excluded from the digital environment, which further widens generational disparities in the labour market.

## 6. CONCLUSIONS

The aim of this study was to carry out a comprehensive assessment of how digital technologies contribute to the economic and social sustainability of rice production. To meet this objective, a quantitative study based on a questionnaire survey was conducted using purposive sampling among representatives of rice-growing enterprises in Kazakhstan, particularly in the Kyzylorda region. The sample consisted of 152 respondents. The questionnaire included five sections covering demographic characteristics, the level of digital technology use, their socio-economic and environmental impacts, perceptions of these technologies, and the institutional support for their implementation.

Based on the literature review, five hypotheses were formulated. Four of them were tested using correlation analysis (Spearman's rank R) and regression analysis, while the fifth hypothesis was examined with the Kruskal–Wallis test. The empirical results confirmed hypotheses H1, H2, H4, and H5, whereas hypothesis H3 was not supported. The findings indicate that higher levels of digital technology adoption are statistically associated with more favourable employees' perceived production outcomes, including crop yield and total harvest volume (H1), as well as with more favourable perceived profitability outcomes in rice-producing enterprises (H2). Hypothesis H3, concerning a reduction in perceived physical workload, was not supported; instead, higher levels of digital technology adoption were associated with a higher perceived physical workload. The results also supported H4, indicating a statistically significant association between the adoption of digital technology and perceived workforce reductions in rice-producing enterprises.

Additionally, the Kruskal–Wallis test indicated statistically significant differences across age groups in employees' perceived ability and readiness to use, learn, and adapt to digital technologies. Higher levels were observed among younger employees, whereas lower levels were observed

among older workers. However, these age-group differences should be interpreted with caution, as none of the pairwise comparisons remained statistically significant after Bonferroni adjustment (H5).

Despite the statistically significant and substantively interpretable results, this study has several limitations. First, the empirical database was created based on survey data, which involves respondents' subjective evaluations. Key indicators of digitalisation levels, along with financial and social effects, were presented as composite indices derived from Likert-scale measurements, thereby reflecting employees' perceptions rather than objective accounting or production data. Second, the reliance on predominantly bivariate regression models limits the capacity to control for other factors such as enterprise size, management capability, or access to investment, which may also influence economic and social outcomes.

Because respondents were recruited from five enterprises, within-enterprise clustering cannot be entirely ruled out. Given the small number of enterprise-level clusters, multilevel estimation was not used. Therefore, the survey findings are interpreted as employee-level perceptions within the five participating enterprises rather than as independent enterprise-level observations.

**Scope of sustainability assessment.** The sustainability-related evidence in this study is limited primarily to the economic and social outcomes analysed using the survey instrument. The questionnaire also included an item on perceived environmental effects of digital technologies; however, the environmental dimension was not developed as a separate empirical outcome in the present analysis. Therefore, the study does not provide a comprehensive empirical assessment of environmental sustainability. In addition, long-term economic viability, employment quality, and distributional outcomes were not directly measured. These dimensions remain important areas for future research, using objective environmental, financial, labour-related, and enterprise-level indicators and longitudinal data.

Several potentially relevant factors were omitted from the regression models. In particular, farm size, irrigation conditions, capital intensity, and mechanisation were not measured with sufficient detail to be included as standardised control variables. These factors may also be related to digital technology adoption and perceived outcomes and could therefore be considered in future research. Future studies could address this limitation by using more detailed enterprise-level data and incorporating a broader range of control variables.

The findings enable the formulation of several recommendations. For future academic research, it would be beneficial to conduct comparable empirical studies in other developing and post-Soviet countries to identify both universal patterns and regional particularities of digitalisation in rice production. Additionally, further research could focus on analysing the varying effects of digitalisation depending on farm size, levels of human capital, and the technological maturity of enterprises.

From a practical standpoint, the findings highlight the importance of viewing digitalisation as a strategic approach to enhancing the efficiency and competitiveness of rice-growing businesses. For policymakers, this underscores the need to combine technological modernisation programmes with initiatives aimed at developing digital skills and workforce retraining. Rice-growing enterprises are advised to adopt phased strategies for implementing digital solutions, aligning them with objectives related to productivity increases and cost reduction. Particular care should also be taken to address the social impacts of digitalisation, including changes to labour roles and the risks linked to employment reductions.

The findings of this study could prove valuable for public authorities in designing digital transformation initiatives in agriculture, for managers of rice-producing companies in developing strategies for technological advancement, and for researchers in the fields of agricultural economics and sustainable development as an empirical and methodological foundation for further comparative research.

Data Availability Statement. The anonymised survey data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to applicable ethical and confidentiality restrictions.

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## APPENDIX

Dear Respondent,

I, Zhanna Smagulova, am conducting a survey as part of my doctoral dissertation on the topic: *"Digital Technologies in Rice Farming: Adoption Experience, Effects, and Institutional Support."*

The aim of the study is to assess the impact of digital technologies on the efficiency and sustainability of enterprise operations through a survey. Participants are asked to answer the questions below. The survey will take approximately 20 minutes.

We kindly ask you to answer the questions. Participation in this study may benefit agricultural (rice-farming) enterprises, society as a whole, individual sectors of the economy, and, in some cases, the survey participants themselves.

The survey will take no more than 20 minutes of your time. Your participation is entirely voluntary. The results of the survey will be presented in the final work (scholarly article, publication) in anonymised form.

If you have any questions or comments regarding this research project, please contact the project supervisor: Zhanna Baglanovna Smagulova, +7 701 288 6492, Smagulova-Zhanna@korkyt.kz.

**I have read the terms of the survey and agree to participate in it.**

**Section A. Demographic Characteristics and Farm Profile**

**1. Age:**

a) 20–25 years; b) 26–35 years; c) 36–45 years; d) 46–55 years; e) 56–65 years; f) 65 years and above

**2. Gender:**

a) Male; b) Female

**3. Education:**

a) Secondary; b) Higher education (bachelor's); c) Postgraduate (master's); d) Postgraduate (doctoral)

**4. Your work experience in agriculture (years):**

a) up to 5 years; b) 5–10 years; c) 11–20 years; d) 21–25 years; e) more than 25 years

**5. Your occupation:**

a) Agronomist; b) Engineer; c) Technologist; d) Worker; e) Accountant; f) Economist; g) Marketing specialist; h) Middle-level manager; i) Senior-level manager

**6. Area of land under rice cultivation at the enterprise where you work:**

a) up to 1,500 ha; b) 1,500–3,000 ha; c) 3,000–4,500 ha; d) 4,500–6,000 ha; e) 6,000–7,500 ha

**7. Legal/ownership form of the enterprise where you work:**

a) Limited liability partnership; b) General partnership; c) Peasant (farm) enterprise

**Section B. Use (Frequency of Use) of Digital and Precision Technologies in Rice Farming**

Please indicate how often you use each of the following, on a scale from 1 to 5, where:

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**8. How often do you use precision farming systems (variable-rate application of fertilisers and plant protection products, parallel driving/auto-steering, yield mapping, and other purposes)?**

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**9. How often do you use sensors and/or monitoring devices (for soil moisture, plant condition, yield monitoring, equipment condition, and other purposes)?**

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**10. How often do you use GPS navigation for route optimisation, tracking the movement of agricultural machinery, field mapping, parallel driving systems, and other purposes?**

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**11. How often do you use drone imagery for monitoring paddy fields, rice spraying, controlling flood-water levels in paddy fields, and other purposes?**

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**12. How often do you use mobile communication and the Internet to access advisory services and information on resources, market prices, weather/climate conditions, and other purposes?**

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**13. How often do you use digital financial services (mobile banking, Internet banking, e-wallets, online loans, etc.) to obtain credit, make payments, and for other purposes?**

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**14. How often do you use e-commerce platforms (purchasing inputs, purchasing fertilisers, selling rice, and other purposes)?**

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**15. How often do you use information systems to obtain subsidies or preferential loans (Unified State Information System of Subsidisation (GISS); the "Auyl Amanaty" rural population lending information system)?**

1 – never; 2 – rarely; 3 – sometimes; 4 – often; 5 – always

**Section C. Economic, Social, and Environmental Effects of Digital Technology (DT) Adoption**

Please indicate your degree of agreement with the following statements, using a scale from 1 to 5, where:

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**When answering, please evaluate outcomes over the past 3 years.**

**16. To what extent do you agree that, over the past 3 years, the use of digital technologies (e.g., precision farming, digital platforms, the Internet) at your enterprise has increased rice yield?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**17. To what extent do you agree that, as a result of using digital technologies (e.g., precision farming, digital platforms, the Internet), gross rice output at your enterprise has increased?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**18. To what extent do you agree that, following the digitalisation of processes at your enterprise, resource savings have occurred (reduced material costs, reduced expenditure on fertilisers and plant protection products, reduced labour costs, etc.)?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**19. To what extent do you agree that, as a result of adopting digital technologies, profit from rice sales has increased?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**20. In your opinion, over the past 5 years, has access to markets (obtaining subsidies and loans, concluding contracts) improved through the use of digital platforms and information systems?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**21. To what extent do you agree that digital technologies have improved environmental indicators (reduced salinisation, preserved soil fertility, water savings, reduced carbon emissions, etc.)?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**22. To what extent do you agree that the shift to digital technologies (sensors, GPS, drones, etc.) has reduced the physical workload at the workplace?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**23. To what extent do you agree that digital solutions (mobile applications, the Internet) have made it easier for you to pursue professional development (online courses, training, seminars, etc.)?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**24. To what extent do you agree that, thanks to digital solutions, you have begun participating more often in discussions and decision-making at your enterprise?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**25. To what extent do you agree that, as a result of the adoption and use of digital technologies at your enterprise, workforce reductions have occurred?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**Section D. Perception of Technology**

**26. To what extent do you agree that it was easy for you to master the innovative technologies introduced at your enterprise?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**27. To what extent do you agree that daily use of digital technologies does not cause you difficulties?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**28. To what extent do you agree that the innovative solutions introduced are easy to combine with the equipment and infrastructure already in place at your enterprise?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**29. To what extent do you agree that digital solutions fit well with your current practice?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**30. To what extent do you agree that you trust the recommendations generated by digital systems / AI?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**31. To what extent do you agree that you are willing to try new agricultural/digital technologies earlier than others?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**32. To what extent do you agree that you are willing to invest time and resources in learning new technologies?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**Section E. Institutional Support for the Adoption and Uptake of Digital Technologies**

**33. To what extent do you agree that you have access to all the digital technologies necessary to perform your duties?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**34. To what extent do you agree that the level of Internet access at your enterprise and/or in the field is sufficient for stable, uninterrupted work/performance of your duties?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**35. To what extent do you agree that you are confident in the confidentiality and security of the data used when working with digital technologies at your enterprise?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**36. To what extent do you agree that you have been provided with opportunities for training and professional development in digital technologies over the past 12**

**months?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**37. In your opinion, does your enterprise create opportunities (pilot projects, demonstration plots) for the practical mastery and testing of new digital technologies?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**38. To what extent do you agree that digital technologies are being introduced at your enterprise through government programmes and subsidies?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**39. To what extent do you agree that the management of the enterprise where you work is planning to expand the use of innovative technologies next year/season?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**40. To what extent do you agree that the enterprise's management is prepared to allocate part of the budget to the digitalisation of production processes?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**41. To what extent do you agree that the management of the enterprise where you work plans to continue acquiring and adopting innovative solutions?**

1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree

**Table A1.** Sources and adaptation of questionnaire items

| Questions | Source | Changes Made |
|---|---|---|
| Section A, Q1, Q2, Q3, Q7, Q5 | Q 2.2, 2.3, 2.5, 2.6, 2.8 (Luque-Reyes, J. R., Zidi, A., Peña-Acevedo, A., & Gallardo-Cobos, R. (2025). Assessing Agri-Food Digitalization: Insights from Bibliometric and Survey Analysis in Andalusia. World, 6(2):57. | Adapted with wording modified to reflect the context of rice-producing enterprises. |
| Section B | Q 4.1 (Luque-Reyes, J. R., Zidi, A., Peña-Acevedo, A., & Gallardo-Cobos, R. (2025). Assessing Agri-Food Digitalization: Insights from Bibliometric and Survey Analysis in Andalusia. World, 6(2):57. | Adapted with wording modified to reflect the context of rice-producing enterprises. |
| Section C | Q 3.3, 5.2 (Luque-Reyes, J. R., Zidi, A., Peña-Acevedo, A., & Gallardo-Cobos, R. (2025). Assessing Agri-Food Digitalization: Insights from Bibliometric and Survey Analysis in Andalusia. World, 6(2):57. | Adapted with wording modified to reflect the context of rice-producing enterprises. |
| Section D | Q 3.1, 3.2, 5.3 (Luque-Reyes, J. R., Zidi, A., Peña-Acevedo, A., & Gallardo-Cobos, R. (2025). Assessing Agri-Food Digitalization: Insights from Bibliometric and Survey Analysis in Andalusia. World, 6(2):57. | Adapted with wording modified to reflect the context of rice-producing enterprises. |
| Section E | Q 4.2 (Luque-Reyes, J. R., Zidi, A., Peña-Acevedo, A., & Gallardo-Cobos, R. (2025). Assessing Agri-Food Digitalization: Insights from Bibliometric and Survey Analysis in Andalusia. World, 6(2):57. | Adapted with wording modified to reflect the context of rice-producing enterprises. |