# ARTIFICIAL INTELLIGENCE IN AGRICULTURE: THE IMPACT ON LABOR PRODUCTIVITY

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A B S T R A C T

The last few years have seen the artificial intelligence technologies' potential to radically transform many industries, including agriculture, by optimizing the use of resources, increasing productivity, work efficiency, and resistance to climate change. The basic research question here is the degree of connection between the level of productivity in agriculture, on the one hand, and the degree of acceptance of AI technologies and a number of agriculture-related economic indicators, on the other hand. For this purpose, an empirical data analysis was carried out for EU 27 member countries. The results of the analysis show a moderately strong positive relationship between the level of the Labor Productivity in Agriculture and the AI Readiness Index score. Also, there is a statistically significant, but slightly less pronounced, positive relationship between the level of the Labor Productivity in Agriculture and GDP per capita and Agriculture, Forestry, and Fishing, Value Added (current US$) in Millions.

## Introduction

The last few years have witnessed a very rapid development in the field of Artificial Intelligence (AI). AI technologies have the potential to radically transform various industries, including agriculture, as well as the functioning of the public sector. These technologies can be labeled as "game-changer" technologies, because in addition to improving existing business models and processes, they can lead to disruptive innovations, i.e. radical changes in the usual business models and business rules in

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an industry. Different definitions of artificial intelligence can be found in literature, depending on the approach to this broad and complex field, which is constantly developing. In particular, this is the definition offered by the expert group of the European Commission: „Artificial intelligence (AI) refers to systems that show reasonable, intelligent behavior based on the analysis of their environment and make decisions – with a certain degree of autonomy – to achieve specific goals" (2020–2025 Strategy for the Development of Artificial Intelligence in the Republic of Serbia, p. 5).

AI encompasses a variety of technologies, including machine learning, deep learning, computer vision and shape recognition, as well as robotics. The essence of machine learning is algorithms based on learning from data, not on explicit programming. Deep learning, as a subset of machine learning, uses multi-layer neural networks to analyze complex data sets, achieving high accuracy in tasks such as image and speech recognition. Computer vision uses machine learning and deep learning techniques and allows computers to interpret visual data from the world, facilitating applications related to object recognition and motion tracking.

AI technologies have "general purpose" characteristics, i.e. they are generic in nature, much like electricity or railroads, or like the steam engine once was. This indicates that the application of these technologies "permeates all areas of the economy and society and introduces revolutionary changes in many of them" (2020–2025 Strategy for the Development of Artificial Intelligence in the Republic of Serbia, p. 5). Particularly suitable areas of AI application are transport, energy, telecommunications, medicine, agriculture and a wide range of public services (Ibid., p. 6).

AI offers numerous opportunities to improve agricultural production, optimize resources, and improve the efficiency of agricultural operations (Nguyen, et. al., 2020; Javaid, et. al., 2023; Mishra, et.al., 2024; Stamenković et al., 2024). The application of AI technologies allows farmers to make decisions based on relevant information, increase yields, reduce costs, and better respond to challenges such as climate change. Also, AI in agriculture has "the potential to feed a continuously growing global population and still contribute to achieving the UN's Sustainable Development Goals (SDGs)" (Ryan et.al., 2023).

In addition to the above, the integration of AI in agriculture can lead to the development of new business models and services (Cavazza et al., 2023). For example, AI-based platforms can offer subscription-based services for crop monitoring and management, providing farmers with relevant recommendations and real-time data. This can attract tech-savvy entrepreneurs and investors, further boosting the agricultural economy. In addition, AI can facilitate better supply chain management, reduce waste and improve the efficiency of agricultural markets. These economic benefits highlight the potential of AI to transform agriculture into a more profitable and sustainable industry. The introduction of AI technologies not only increases productivity, but also makes agriculture more sustainable and resistant to future challenges (Dolgikh, Mulesa, 2021).

Bearing in mind the previously stated views and observations, the question arises as to how the impact of AI technologies on increasing labor productivity in agriculture can be seen (and measured), taking into account the macro level, i.e. state level? This was the core research question in this paper.

It is generally accepted that the basic indicator of the readiness of countries to accept and apply AI is the AI Readiness Index. It is a composite index that includes 39 indicators, divided into three groups: government indicators (12 indicators), technology sector indicators (15 indicators), and data and infrastructure indicators (12 indicators) (Government AI Readiness Index 2023).

The paper analyzes the connection of labor productivity in agriculture with the AI readiness index, as well as with a series of economic indicators at the macro level. The research is focused on EU member states. The derived conclusions are then connected to the situation in Serbia, where basic comparisons of trends in the AI readiness index were made for Serbia and several EU member states with similar geographic and demographic characteristics. Based on the obtained empirical results, concluding comments are given.

## Literature review

AI with all its technologies, has significant potential to improve and modernize agriculture, providing advanced tools to increase efficiency and productivity in this sector. Eli-Chukwu (2019) provides a comprehensive overview of AI applications in agriculture, highlighting the various techniques and technologies used to optimize agricultural processes. This author indicates that the application of AI in agriculture brings numerous benefits, including improving yields, optimizing resources and reducing costs. Subeesh and Mehta (2021) point out that AI and IoT can revolutionize agriculture by automating tasks such as irrigation, pesticide application and crop monitoring. Their research shows that these technologies enable precise management of resources, thereby reducing operating costs and increasing production efficiency.

As explained in the study (Dharmaraj, Vijayanand, 2018), the direct application of AI or machine intelligence in the agriculture sector clearly indicates changes in the way agriculture is practiced today. AI-based agriculture solutions allow farmers to be more efficient with less investment of time and resources, improving quality and providing a quick go-to-market strategy. The integration of cognitive computing in agriculture enables systems to mimic human thought processes, making decisions that improve crop yields, manage resources more efficiently and reduce the need for manual labor.

Machine learning technologies bring benefits to agriculture in the area of crop management, livestock management, water management and soil management (Liakos, et al., 2018). A similar overview of the application of machine learning in agriculture can be found in the paper written by Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021).

Radun, Dokić and Gantner (2021) explore the specific application of AI in livestock, emphasizing the AI contribution to precise livestock production. Using AI technologies, such as sensors and algorithms for data analysis, it is possible to monitor livestock health, optimize nutrition and improve reproductive processes, all of which contribute to sustainable and efficient milk and meat production.

Kovljenic et al. (2023) provide insight into the application of these technologies on farms in AP Vojvodina, where digital tools contributed to improving productivity and farm management. Their research shows that the use of digital technologies can help accurately monitor crops, predict yields and optimize the use of fertilizers and pesticides.

Rudrawar (2024) emphasizes the potential of AI in terms of transforming the agricultural sector through the introduction of innovative solutions that can improve all aspects of food production. His work explores how AI can contribute to more efficient management of agricultural operations, reducing waste and improving product quality. Also, Rudrawar emphasizes the importance of cooperation between researchers, technologists and farmers for the successful implementation of AI technologies. Ben Ayed and Hanana (2021) focus on improving the food and agriculture sector through AI, while Zha (2020) explores the application of AI in agriculture, providing a comprehensive overview of current achievements and future perspectives.

Talaviya et al. (2020) explore the application of AI to optimize irrigation and pesticide and herbicide application, pointing to opportunities to improve efficiency and reduce negative environmental impacts. On the other hand, Mladenović, I. and Mladenović, S.S. (2023) analyze the contribution of the agricultural sector to the economic growth of the EU 27 countries, emphasizing the importance of innovation and state incentives.

The application of AI in agriculture includes several innovative methods that transform traditional agricultural practices (Adewusi et al., 2024). AI is used in precision agriculture, where it processes data from various sources, such as weather conditions, soil quality and crop health, to create real insight into the condition (Kostić, 2021). This enables precise interventions, optimization of resource use and increased crop yields.

Finally, Mihailović, Radosavljević and Popović (2023) focus on the role of smart gardens in urban environments. Their research shows that smart gardens, which use AI to optimize plant growing conditions, can significantly contribute to sustainable food production in cities. These technologies make it possible to grow fresh vegetables and fruits all year round, reduce the need to transport food and improve access to fresh food in urban areas.

The above papers provide an overview of the current state and potential of AI application in agriculture. Highlighting the diverse applications of AI, from automating tasks to optimizing production processes, they highlight the key benefits the technology brings to the agricultural sector. With innovative solutions and collaboration among different actors, AI has the potential to significantly improve the efficiency, sustainability and productivity of agricultural practices around the world.

## Current AI trends in the agricultural market

As pointed out in the introductory part, AI includes modern technologies that have a disruptive significance and a strong influence on the transformation of entire industrial branches. This also applies to the agricultural sector. It is no exaggeration to say that AI has the potential to revolutionize agricultural processes and activities. The main goal of these changes is to increase productivity and efficiency in the agricultural sector.

The latest research indicates that the application of AI in agriculture is on the rise, with an average global growth rate of 24.5% in the last decade (AI in Agriculture Statistics, 2024). In 2022, the global value of AI in agriculture market was US$ 1.2 billion and expected to reach US$ 10.2 billion in 2032. The aforementioned research indicates the most important components of the AI in agriculture market, shown in table 1.

**Table 1.** Market Share of AI Components in Agriculture

| Component | Market Share (%) |
|---|---|
| Software | 45.2 |
| Hardware | 24.5 |
| Service | 18 |
| AI-as-a-Service | 12.3 |

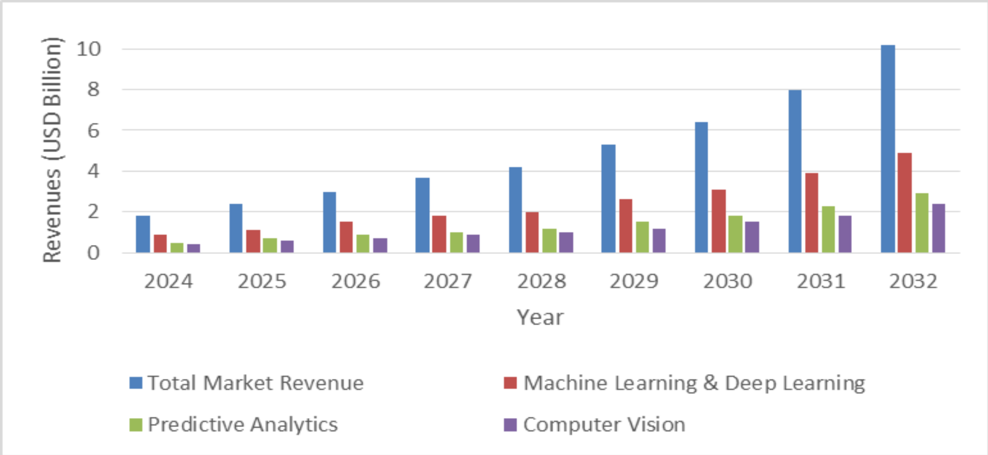
*Source*: AI in Agriculture Statistics: Transforming Farming Practices for Enhanced Efficiency and Sustainability

Table 1 clearly shows that software dominates the market with a share of 45.2%, which highlights the key role of software solutions in the transformation of agricultural practices. Software applications in agriculture enable big data analysis, resource optimization and process automation, leading to increased efficiency and productivity. Data-driven AI methods are becoming increasingly popular due to their high efficiency, especially with the advent of large-scale datasets and high-performance computing units (Su et al., 2023). Hardware is also significant, with a share of 24.5%, indicating the importance of physical infrastructure supporting AI implementations. This segment includes sensors, drones and robotic systems that collect data and perform physical tasks on farms. Services have a share of 18.0%, indicating a high demand for professional services that help in the adoption of AI technologies. Consulting services, training and implementation support play a key role in enabling farmers to use AI technologies effectively. Finally, AI-as-a-service, with a share of 12.3%, reflects the growing popularity of cloud-based AI solutions that offer scalability and affordability for agricultural enterprises. These solutions allow farmers to use advanced AI tools without the need for large initial investments in infrastructure.

Based on the previously presented data, key areas of investment and development in the agricultural sector can be identified. Understanding the market share of various AI components helps decision makers, researchers and investors recognize trends and opportunities to improve the efficiency and sustainability of agricultural production.

Figure 1 shows the growth projection of AI in Agriculture Market Revenue in 2024–2032. The total market value is shown in detail, divided according to the representation of certain technologies: machine and deep learning, predictive analytics, and computer recognition of shapes and patterns.

**Figure 1**. Projected Growth of AI in Agriculture Market Revenue (2024–2032)




*Source*: AI in Agriculture Statistics: Transforming Farming Practices for Enhanced Efficiency and Sustainability

As seen in the previous graph, total market revenues are expected to grow drastically, highlighting the growing economic impact of AI in improving the efficiency and sustainability of agriculture. The data presented depicts a significant jump in Total Market Revenue from $1.8 billion in 2024 to $10.2 billion in 2032, which clearly indicates increasing investment and innovation in this sector. Revenues from machine and deep learning, predictive analytics, and computer vision are projected to grow significantly, contributing to overall market growth and providing additional opportunities to improve agricultural practices.

## Empirical analysis

### *Data and methodology*

In the introductory part of the paper, we pointed out that the main research question in this paper is the discovery of the degree of connection between the level of labor productivity in agriculture and the degree of acceptance of AI technologies by the governments, as well as a series of economic indicators important for the agricultural field. For this purpose, an empirical data analysis was carried out, where parametric correlation and regression analysis techniques were applied. The analysis was conducted for 27 member countries of the European Union (EU). The following indicators are included in the analysis: *Labor Productivity in Agriculture (EUR/FTE)*, a variable that is presented as a dependent variable in the regression model, as well as the following indicators as independent predictor variables:

*Rural Development Financial Contribution to Restructuring and Modernization (%), AI Readiness Index*, *Network Readiness Index*, *GDP per capita (current US$)*, *Agriculture, Forestry, and Fishing, Value Added (current US$) in Millions,* and *Agriculture, Forestry, and Fishing, Value Added (% of GDP).* The data were taken from official databases and reports of institutions that monitor the above indicators: data on *Labor Productivity in Agriculture (EUR/FTE)* and *Rural Development Financial Contribution to Restructuring and Modernization (%)* were taken from the report of the European Commission – Directorate-General for Agriculture and Rural Development; data on AI Readiness Index from Oxford Insights Reports (Government AI Readiness Index); data on the *Network Readiness Index* from regular annual reports on this index prepared by the Portulans Institute, University of Oxford and Saïd Business School; data on other indicators were taken from the World Bank databases (World Bank indicators and Open Data).

The data refer to the year 2022. The analysis was carried out using the IBM SPSS software package and the R programming language.

## Results

As we previously pointed out, according to the subject and goal of the research, as well as the type and nature of the observed data, parametric techniques of correlation and regression analysis were applied in the analysis. First, a correlation analysis of the observed variables was conducted. The results are shown in Table 2 and Table 2a.

**Table 2.** Correlation – Pearson correlation coefficients (2022)

| | LPA | RDF | AIRI | NRI | GDP p. c. | AFF v. a. | AFF % GDP |
|---|---|---|---|---|---|---|---|
| LPA | 1.000 | -0.127 | 0.703 | 0.762 | 0.583 | 0.412 | -0.556 |
| RDF | -0.127 | 1.000 | -0.098 | -0.100 | -0.041 | -0.266 | 0.135 |
| AIRI | 0.703 | -0.098 | 1.000 | 0.892 | 0.472 | 0.372 | -0.523 |
| NRI | 0.762 | -0.100 | 0.892 | 1.000 | 0.575 | 0.219 | -0.665 |
| GDP p. c. | 0.583 | -0.041 | 0.472 | 0.575 | 1.000 | -0.018 | -0.676 |
| AFF v. a. | 0.412 | -0.266 | 0.372 | 0.219 | -0.018 | 1.000 | -0.095 |
| AFF % GDP | -0.556 | 0.135 | -0.523 | -0.665 | -0.676 | -0.095 | 1.000 |

*Source*: Authors' calculations

**Table 2a.** Correlation – Pearson correlation coefficients – Sig. (p value) (2022)

| | LPA | RDF | AIRI | NRI | GDP p. c. | AFF v. a. | AFF % GDP |
|---|---|---|---|---|---|---|---|
| LPA | | 0.264 | 0.000 | 0.000 | 0.001 | 0.016 | 0.001 |
| RDF | 0.264 | | 0.313 | 0.311 | 0.420 | 0.090 | 0.252 |
| AIRI | 0.000 | 0.313 | | 0.000 | 0.007 | 0.028 | 0.003 |
| NRI | 0.000 | 0.311 | 0.000 | | 0.001 | 0.137 | 0.000 |
| GDP p. c. | 0.001 | 0.420 | 0.007 | 0.001 | | 0.464 | 0.000 |
| AFF v. a. | 0.016 | 0.090 | 0.028 | 0.137 | 0.464 | | 0.320 |
| AFF % GDP | 0.001 | 0.252 | 0.003 | 0.000 | 0.000 | 0.320 | |

*Source*: Authors' calculations

Key:

LPA – Labour Productivity in Agriculture (EUR/FTE)

RDF – Rural Development Financial Contribution to Restructuring and Modernization (%)

AIRI – AI Readiness Index

NRI – Network Readiness Index

GDP p. c. – GDP per capita (current US $)

AFF v. a. – Agriculture, Forestry, and Fishing, value added (current US$) in millions

AFF % GDP – Agriculture, Forestry, and Fishing, value added (% of GDP)

Based on the data in Table 2 and Table 2a moderate and strong correlation between the variable *Labor Productivity in Agriculture* and other variables can be observed. It is mainly a positive correlation, with the exception of the correlation between *Labor Productivity in Agriculture* and *Agriculture, Forestry, and Fishing, Value Added (% of GDP),* where a statistically significant negative correlation coefficient was recorded (-0.556, p=0.001), as well as correlation between *Labor Productivity in Agriculture* and the indicator *Rural Development Financial Contribution to Restructuring and Modernization (%)*, where a negative correlation was recorded (-0.127), which is not statistically significant (Sig. p=0.264).

Based on the correlation analysis, a regression analysis was carried out, where three linear regression models were applied (Soldić-Aleksić, J, 2018):

**Model 1**: LPA was regressed on all other indicators:

LPA = -91582.14 + 5431.38 RDF – 377.23 AIRI + 1940.18 NRI + 0.251 GDP p. c. + 0.517 AFF v. a. + 1053.81 AFF % GDP

Model 1 is characterized by the following global statistics: coefficient of determination $R^2 = 0.699$; Std. Error of the Estimate = 13633.97 (in comparison with Std. Deviation of LPA = 21808.17) and ANOVA test (F = 7.754, df = 6, 20, Sig. = 0.000) which indicate the statistical significance of the obtained model. However, a more detailed analysis shows the following: the t test indicates the statistical significance of the regression coefficients only for the indicators of NRI and AFF v. a. (Sig. for the predictors are respectively: 0.878, 0.668, 0.054, 0.095, 0.033, and 0.772). Also, high multicollinearity of indicators AIRI and NRI, as well as AFF v. a. and AFF % GDP was observed (VIF values are respectively: 6.127, 7.151, 1.384, and 2.454). Therefore, we excluded the NRI and AFF % GDP indicators from Model 1.

**Model 2**: LPA was regressed on the following indicators: RDF, AIRI, GDP p. c. and AFF v. a.

LPA = -64852.72 + 131.49 RDF + 1203.81 AIRI + 0.321 GDP p. c. + 0.411 AFF v. a.

The resulting Model 2 has the following global features: coefficient of determination $R^2$ = 0.631; Std. Error of the Estimate = 14392.60 (in comparison with Std. Deviation of LPA = 21808.17) and the ANOVA test (F = 9.424, df = 4, 22, Sig. = 0.000) which indicate the statistical significance of the obtained model. In model 2, multicollinearity is not present (VIF values for predictors RDF, AIRI, GDP p. c. and AFF v. a. are respectively: 1.079, 1.582, 1.366, and 1.314). The t test that checks the statistical significance of regression coefficients in Model 2 shows that regression coefficients with the variables AIRI and GDP p. c. are statistically significant (Sig. for the predictors are: 0.997, 0.017, 0.017, and 0.090, respectively). Also, the standardized regression coefficients (Beta coefficients) in this model for the predictors RDF, AIRI, GDP p. c., and AFF v. a. are the following: 0.000, 0.421, 0.389, and 0.263 respectively. It is obvious that the RDF indicator can be excluded from Model 2.

**Model 3**: LPA was regressed on the following indicators: AIRI, GDP p. c. i AFF v. a.

LPA = -64833.49 + 1203.86 AIRI + 0.321 GDP p. c. + 0.411 AFF v. a.

The coefficient of determination remained the same as in Model 2 ($R^2$ = 0.631); Std. Error of Estimate is slightly lower compared to Model 2 and amounts to 14076.25; The ANOVA test shows that the obtained model is statistically significant: F = 13.136, df = 3, 23, Sig. = 0.000. The VIF values for the predictors are respectively: 1.580, 1.362 and 1.229, indicating no multicollinearity. Based on the values of the correlation coefficients (0.703, 0.583, and 0.412) and the values of the Beta regression coefficients (0.421, 0.389, and 0.263) for the predictors in this model, it can be concluded about the strongest influence of the AI Readiness index on the observed dependent variable LPA – *Labor Productivity in Agriculture (EUR /FTE)*.

Since these are three models that have the features of a nested model, the ANOVA test was applied for their comparison. The results of ANOVA analysis are: ANOVA (Model 2, Model 1): p = 0.1305; ANOVA (Model 3, Model 2): p = 0.9972. Also, in order to compare the above three models, the Akaike Information Criterion (AIC) values were calculated for each model: AIC (Model 1) = 598.6171; AIC (Model 2) = 600.1146; AIC (Model 3) = 598.1146 (Kabacoff, 2015, p. 202). The obtained results clearly indicate the advantages of Model 3 compared to Model 1 and Model 2.

Table 3 shows the summary results obtained for the previous three regression models.

**Table 3.** Summary Results – main models' statistics

| Statistics | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| $R^2$ | 0.699 | 0.631 | 0.631 |
| Std. Error of the Estimate | 13633.97 | 14392.60 | 14076.25 |
| ANOVA test | F = 7.754, df = 6, 20, Sig. = 0.000 | F = 9.424, df = 4, 22, Sig. = 0.000 | F = 13.136, df = 3, 23, Sig. = 0.000. |
| Multicollinearity (VIF) | expressed (1.099; 6.127; 7.151; 2.004; 1.384; 2.454) | not expressed (1.079; 1.582; 1.366; 1.314) | not expressed (1.580; 1.362; 1.229) |

| Statistics | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Model comparisons: ANOVA test | | ANOVA (Model 2, Model 1): p = 0.1305 | ANOVA (Model 3, Model 2): p = 0.9972 |
| AIC* | 598.6171 | 600.1146 | 598.1146 |

*Akaike Information Criterion

*Source*: Authors' calculations

Based on the results of the empirical analysis, it can be concluded that there is a strong connection between the level of the *AI Readiness Index* and the *Labor Productivity in Agriculture*. Furthermore, the relationship, i.e. the influence of the *GDP per capita* indicator and the *Agriculture, Forestry, and Fishing, Value Added (current US$) in Millions* indicator on the variable *Labor Productivity in Agriculture* is somewhat weaker.

## The position of Serbia

Bearing in mind the results of the previous data analysis, which revealed a significant connection between the level of the AI readiness index and productivity in the agricultural sector, below is a presentation of the trend in the value of this index for Serbia and five EU member states that we singled out due to certain geographic and/or demographic similarities with Serbia.

First of all, let us point out that in terms of most of the indicators included in the previous analysis, with the exception of the indicator *Agriculture, Forestry, and Fishing, Value Added (% of GDP)*, Serbia lags behind the average of EU countries (Table 4).

**Table 4.** Values of the analyzed indicators for Serbia and EU countries – average (2023)

| | AIRI | NRI | GDP p. c. | AFF v. a. | AFF %GDP |
|---|---|---|---|---|---|
| Serbia | 55.57 | 51.68 | 11361.00 | 3935.74 | 5.20 |
| EU average | 65.87 | 63.85 | 42248.34 | 11448.67 | 2.11 |

*Source*: Oxford Insights, Portulans Institute, World Bank official reports and authors' calculations

Key:

AIRI – AI Readiness Index

NRI – Network Readiness Index

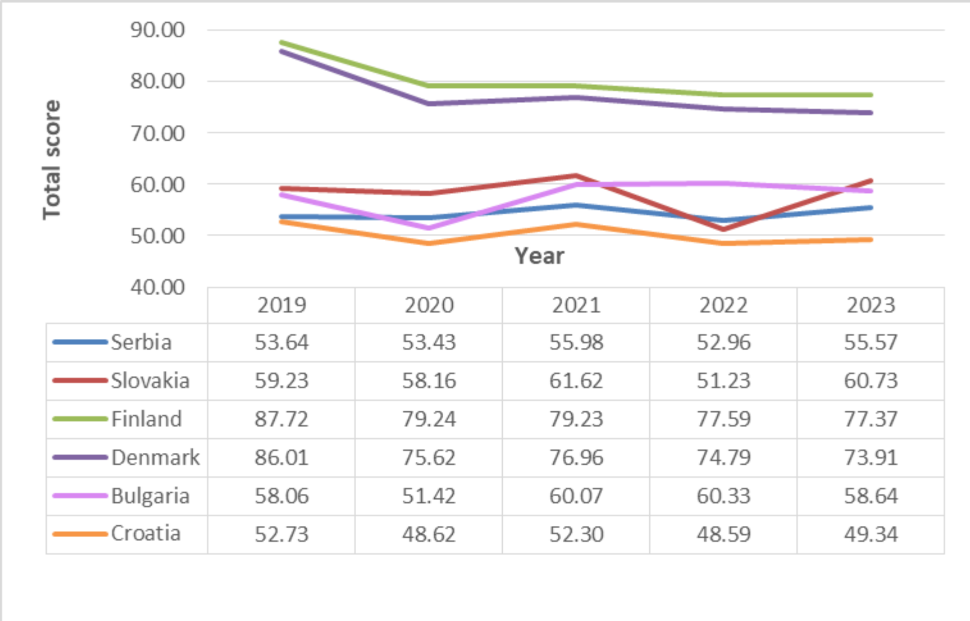
GDP p. c. – GDP per capita (current US $)

AFF v. a. – Agriculture, Forestry, and Fishing, Value Added (current US$) in Millions

AFF % GDP - Agriculture, Forestry, and Fishing, Value Added (% of GDP)

The values of the AI Readiness Index in 2019–2023 highlight the changing picture of readiness for the application of AI among European countries such as Slovakia, Finland, Denmark, Bulgaria, Croatia, and Serbia (Government AI Readiness Index Reports for 2019, 2020, 2021, 2022, and 2023).

**Figure 2.** Comparative Analysis of AI Readiness Scores (2019–2023)




| | 2019 | 2020 | 2021 | 2022 | 2023 |
|---|---|---|---|---|---|
| Serbia | 53.64 | 53.43 | 55.98 | 52.96 | 55.57 |
| Slovakia | 59.23 | 58.16 | 61.62 | 51.23 | 60.73 |
| Finland | 87.72 | 79.24 | 79.23 | 77.59 | 77.37 |
| Denmark | 86.01 | 75.62 | 76.96 | 74.79 | 73.91 |
| Bulgaria | 58.06 | 51.42 | 60.07 | 60.33 | 58.64 |
| Croatia | 52.73 | 48.62 | 52.30 | 48.59 | 49.34 |

*Source*: Authors' calculations based on data from multiple Oxford Insights reports

Based on the data for the year 2023, it is evident that Serbia lags behind the value of the AI Readiness Index compared to the average of EU countries by more than 10 points (Table 4). Figure 2 reveals trends in the movement of the AI readiness index for Serbia and several selected EU countries. Also, it is noted that Serbia shows a gradual improvement in its readiness to accept AI technologies, increasing its AI score from 53.64 in 2019 to 55.57 in 2023. A similar tendency can be observed for Slovakia and Bulgaria. It is interesting to note a marked drop in the AI index for Finland and Denmark in 2023 compared to 2019: for Finland, the AI index in 2023 is lower compared to 2019 by over 10 points, and for Denmark by more than 12 points. Despite the decline, Finland and Denmark remain leaders among EU countries. Monitoring the movement of the AI index is especially important for countries like Serbia that are trying to catch up with more advanced countries. By learning from the successful strategies of leading countries, Serbia can improve its adoption of AI technologies and use AI technologies to drive economic growth and innovation in agriculture and other key sectors.

## Conclusion

In this paper, we considered the connection between labor productivity in the agricultural sector and the general development and applicability of AI at the macro level. The results of the empirical analysis for EU countries show a strong connection between the *Labor Productivity in Agriculture* and the *AI Readiness Index* at the national level. It is interesting that this connection is more pronounced compared to the connection of the *GDP Per Capita* indicator and indicator *Agriculture, Forestry, and Fishing, Value Added (current US$) in Millions,* with the variable *Labor Productivity in Agriculture*. The obtained result unequivocally indicates the importance of improving the entire AI ecosystem at the national level (three important AI pillars: government pillar, technology sector pillar and data and infrastructure pillar), which generally leads to conditions for increasing productivity in the agricultural sector.

Moderate growth of the AI index in the last five years is evident in Serbia. However, Serbia still lags behind the average value of the AI index in EU countries, which indicates the need for further investments in digital infrastructure, AI research and development, and reform policies to accelerate the adoption of AI technologies.

As AI technologies continue to develop, their application in agriculture is likely to expand, offering even greater opportunities to improve agricultural outcomes and contribute to the broader goal of sustainable development. The insights provided here are intended to help define a strategy that will support the integration of AI in agriculture, ensuring a sustainable and prosperous future for the Serbian agricultural sector.

## Conflict of interests

The authors declare no conflict of interest

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