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A Cross-Sectional Analysis of the Relationship between Digital Technology Use and Agricultural Productivity in EU Countries

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Abstract: Amidst the rapid evolution of digital technologies and their prospective implications for agricultural productivity, farmers are increasingly turning to Agriculture 4.0. As digitization permeates every facet of agriculture, the potential for boosting productivity while ensuring sustainability and resilience becomes increasingly tangible. The objective of this study is to understand how the adoption of digital technologies influences agricultural productivity within the diverse socioeconomic and agricultural landscapes of EU nations. The research of this study aims to address questions concerning the impact of digital technology use on agricultural productivity across EU countries. This study employs a robust analytical framework combining equation modeling (SEM), artificial neural networks, and cluster analysis. SEM analysis reveals significant associations and influences between digital technology use and productivity related to the total labor force across EU countries. Moreover, cluster analysis outlines distinct clusters of EU member states distinguished by varying degrees of digital technology incorporation and corresponding agricultural productivity, emphasizing the diverse socioeconomic contexts that influence these associations. These findings underscore the significance of embracing digital technology as a catalyst for enhancing agricultural productivity across EU nations. Future research could focus on devising strategies to promote the widespread adoption of digital technologies in agriculture across EU member states, and longitudinal analyses could offer insights into the dynamic relationship between digital technology use and agricultural output, informing policy interventions.

Keywords: agriculture; Agriculture 4.0; agricultural productivity; digital technology use

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1. Introduction

The advances in information technology have led to rapid penetration of digital technology across all sectors of the national economy. These technologies are becoming a new engine for stimulating economic growth and driving development [1]. Food and agricultural production confront significant challenges globally, such as ensuring healthy food and clean water for a growing population, combating climate change, and protecting biodiversity [2–4]. In this context, digitization is seen as a promising solution for improving sustainability in the agri-food system. Digital technologies, such as precision agriculture and smart farming, have the potential to mitigate the negative impact of agriculture on the environment and increase efficiency and productivity for farmers [5–7]. However, research on the opportunities and challenges of agricultural digitization has only just begun, and its impact on sustainability remains to be established [8].

The digital economy, characterized by the integration of digital network applications and the merging of digital technology with traditional economic systems, has opened up possibilities for the advancement of digitalized agriculture [9–11]. The adoption of cutting-edge agricultural practices, driven by digital technologies, has emerged as a crucial pathway for initiating rural transformation [12]. Digital technologies encompass efforts to enhance resource allocation efficiency, promote innovation in agricultural production, and enhance agricultural productivity [10,13].

Amidst the rapid advancement of digital technologies and their potential implications for agricultural productivity, this study aims to explore the relationship between the adoption of digital technologies and agricultural productivity in the European Union (EU). While previous research has investigated this correlation in various contexts, there is a research gap concerning the agricultural EU landscape. This gap is significant due to the complex and diverse nature of the EU, where the impact of technological advancements may vary greatly depending on each country's specific socioeconomic and agricultural conditions. Therefore, addressing this research gap is crucial for obtaining a comprehensive understanding of how digital technologies can impact agricultural productivity and for developing targeted policies at the EU level. The main objective of this paper is to examine how the adoption of digital technologies influences agricultural productivity across the varied socioeconomic and agricultural landscapes of EU nations.

The novelty and originality of this approach lie in its integration of various analyses, particularly in considering factors such as agricultural productivity rates, the utilized agricultural area, and the agricultural labor force. This comprehensive method offers a deeper understanding of agricultural efficiency and performance by specifically assessing how land resources and labor dynamics influence agricultural production. Moreover, the cross-sectional nature of this study, which explores the relationship between digital technology adoption and agricultural performance across diverse EU countries, adds another layer of distinctiveness. This methodology enables the comparison and identification of variations among member states, providing valuable insights into how specific socioeconomic and agricultural factors shape the impact of digital technologies on agriculture. Furthermore, this paper highlights the digital transformation of agriculture as a significant driver of rural development and sectoral modernization. By embracing digital technologies and innovative practices, the potential for economic growth and enhanced quality of life in rural areas is substantial.

This paper includes six sections. The Section 1 sets the stage for the research issue. The Section 2 consolidates and assesses prior research related to the subject, acting as the theoretical basis for the formulation of hypotheses. Following the Section 2, the Section 3 outlines this study's design and implementation. The Section 4 presents and elucidates the findings derived from data analysis. The Section 5 contextualizes and interprets the results in relation to the existing literature and research questions. Lastly, the Section 6 summarizes the findings along with their broader implications.

2. Literature Review and Hypotheses Development

2.1. Digitization and Its Role in Agriculture

Digitization is transforming human behaviors and can yield positive outcomes both economically and ecologically. However, as underscored by various studies, digital transformation may also give rise to social and ethical concerns [14–17]. Various papers contribute to elucidating these effects, focusing on instances of technology-driven utilization (such as cloud computing, artificial intelligence, Big Data, and the Internet of Things) applied in specific areas [16,18–21]. Besides the favorable economic and ecological impacts of digitization, concerns have arisen regarding the social and ethical implications that this transformation may involve [16,20,21]. Conversely, various research endeavors explore instances of applying digital technologies in agriculture, aiming to present a comprehensive overview of their influence [17].

Digital technologies have transformed the global landscape of agricultural practices and management [22]. The integration of sensors, Big Data, and artificial intelligence in agriculture has empowered farmers to optimize production, reduce expenses, and enhance yields [23–25]. Furthermore, digital technologies have unlocked new possibilities in precision agriculture, where every facet of the production process is finely calibrated to enhance efficiency and mitigate environmental footprint. Hence, digital agriculture assumes a pivotal role in advancing economic, ecological, and social sustainability, contributing to augmenting food production, curbing wastage, and safeguarding natural resources [26].

The digital economy has bolstered resource distribution efficiency, mitigated resource disparities, and propelled advancements in agricultural practices' quality. This transformation has fostered more equitable access to resources and opportunities within the agricultural sector, promoting sustainable growth and development [27]. Data and information serve as crucial production factors in the digital economy. The vast array of data and information disseminated through digital technology facilitates communication and trust among farmers and other entities in the industrial chain, thereby reducing information asymmetry and market transaction costs and enabling the swift development of precision agriculture [28]. Several studies have demonstrated that agricultural enterprises lacking expertise and digital technology incur relatively high production costs due to limited access to databases, outdated software, and information services, potentially resulting in the loss of competitive advantage in local and global markets [1,29–32].

The digitization of agriculture is poised to fundamentally and disruptively transform agri-food systems, albeit with uncertain consequences and social and ecological implications [17,19,33]. The progression of information technologies, including the Internet of Things, artificial intelligence, Big Data, and cloud computing, significantly accelerates this process, ushering in a new era of cyber–physical integration. Consequently, the physical and virtual realms are converging toward the digitization of the entire agricultural value chain, facilitating the development and implementation of dynamic digital representations of real-world systems [34]. This advancement will enable real-time monitoring, direct consumer–producer interaction, and the automation of agricultural processes. Simultaneously, digital infrastructure will become indispensable across all stages of agricultural production and the value chain [35].

The comprehensive utilization of Big Data in the agricultural production chain has the potential to enhance the efficiency and profitability of agricultural operations while furnishing valuable insights for decision-making. Farmers can more effectively discern market trends, optimize production processes, and responsively address consumer demand by aggregating and analyzing data across the entire production chain. Access to timely data and information can bolster farmers' confidence in their business decisions and support their partnerships with stakeholders and consumers [36].

Information platforms dedicated to agricultural products are vital for enhancing transparency and food safety in rural regions [37,38]. These platforms enable consumers to trace the origin and quality of agricultural products, fostering trust in the food supply chain and safeguarding public health. Information regarding agricultural products can be swiftly stored and retrieved, streamlining product tracking and monitoring from farm to consumer. Such capabilities can mitigate risks associated with unsafe food and promote a healthier, more resilient rural environment [39].

Rural data centers and digital agricultural parks serve as crucial infrastructure for facilitating the adoption and integration of digital technology in rural settings. These entities offer access to digital tools and services that aid farmers in farm management, process optimization, and income augmentation [40]. These initiatives contribute to bridging the digital divide between urban and rural areas, thereby promoting digital inclusion and fostering sustainable development within rural communities [41].

2.2. *Agriculture 4.0*

2.2.1. Precision Agriculture and Smart Agriculture

Agriculture 4.0 represents a growing paradigm poised to revolutionize agricultural management and practices [24]. Harnessing digital technologies such as the Internet of Things (IoT), Big Data, agricultural robots, and process automation, Agriculture 4.0 seeks to optimize agricultural production, reduce wastage, and enhance the efficiency, sustainability, and profitability of the entire agricultural sector [42,43]. This evolution not only delivers direct benefits to farmers by augmenting productivity and trimming costs but also enables more agile responses to market demands and aids in achieving societal environmental, economic, and social objectives [44].

Precision agriculture and smart agriculture emerge as pivotal technological trajectories in modernizing the agricultural sector [45,46]. Precision agriculture entails the collection and analysis of precise data to furnish tailored and actionable solutions at the field or plantation level [45]. Conversely, smart agriculture leverages these data to drive intelligent and automated systems, enabling rapid decision-making and the efficient execution of agricultural tasks. Smart agriculture optimizes resource utilization, boosts productivity, and mitigates environmental impact by integrating advanced technologies like sensors, drones, and machine learning algorithms [46]. Both approaches are indispensable in adapting agriculture to contemporary demands and challenges, fostering the sustainable and efficient advancement of the agricultural sector.

Precision agriculture relies on a variety of sensing technologies, including proximity sensing and remote sensing [47]. The integration of these technologies in agriculture promises enhanced resource optimization and heightened operational efficiency [48]. Through sensors and other Internet of Things (IoT) devices, farmers gain access to real-time, detailed information about environmental and production conditions, empowering them to make more informed and precise decisions regarding crop management. Collaborative networks among farmers further facilitate collaboration and drive increased productivity and profitability in the agricultural sector [49].

The convergence of smart farming and precision agriculture heralds new opportunities for modernizing and enhancing efficiency in agricultural practices [35,36]. These two domains synergize, enabling the adoption of more sustainable agricultural practices grounded in advanced digital data and technologies. The digitization of agricultural processes, coupled with the utilization of robotics, automation, and the analysis of vast datasets using machine learning, constitutes critical pillars of this transformation. By leveraging these technologies, farmers can make more informed and precise decisions, optimize resource utilization, and maximize crop yields, thereby fostering economic growth and sustainable development in the agricultural sector [44,50].

2.2.2. Digital Technologies

The incorporation of Industry 4.0 technologies into agriculture has revolutionized the management and execution of agricultural operations. By linking agricultural machinery to the Internet and leveraging artificial intelligence and data analysis, farmers gain access to real-time information on crop conditions, soil health, and other critical factors [25]. These data empower them to make more informed decisions regarding optimal planting timing, irrigation schedules, fertilizer and pesticide applications, and harvest timings. Cloud technologies enable the storage and remote access of these data, facilitating collaboration and information exchange among farmers, researchers, and government agencies. This digital transformation has resulted in increased productivity and sustainability in the agricultural sector [45,46].

The advent of the Internet of Things (IoT) has significantly altered the management of agricultural activities [51]. Through the deployment of sensors and cloud computing, farmers can monitor various vital variables in real time, including soil moisture, temperature, air humidity, and plant health. These data inform the implementation of intelligent and automated solutions, such as sensor-controlled irrigation systems, which deliver precise amounts of water at optimal times, conserving resources and maximizing crop yields [50]. These technologies facilitate swift detection and intervention against pests and diseases, thereby reducing reliance on pesticides and mitigating their environmental impact.

Big Data and machine learning technologies play pivotal roles in the digital transformation of agriculture [52]. By analyzing vast datasets generated by sensors and other sources, farmers gain valuable insights into environmental conditions, crop health, and animal well-being, enabling them to make more informed and efficient decisions regarding farm management [53]. Machine learning algorithms can be employed to develop sophisticated crop management and irrigation systems that optimize resource allocation and yield maximization. Drones and ground vehicles equipped with sensors and high-resolution cameras enable precise monitoring and mapping of agricultural lands, allowing for the swift detection and resolution of issues [35]. These advanced technologies reduce reliance on chemical pesticides and fertilizers, thereby promoting sustainable agriculture and safeguarding the environment.

The adoption of digital technologies in agriculture has spurred the emergence of novel business models aimed at optimizing agricultural processes and enhancing farm efficiency and sustainability [24]. For instance, leveraging IoT sensors and data analytics platforms empowers farmers to monitor environmental conditions in real time and make informed decisions regarding irrigation, fertilization, and crop protection [51,54]. Smart applications can streamline production processes and minimize product losses through efficient supply chain management and distribution [45]. This not only results in increased production and income for farmers but also reduces environmental impact and ensures the long-term sustainability of their operations [53].

Enhancing agricultural productivity is crucial for bolstering farmers' incomes and ensuring food security and economic stability in rural areas. Research on agricultural productivity plays a pivotal role in identifying effective agricultural practices based on new digital technologies. Understanding these aspects can pave the way for the development of improved agricultural policies and practices that foster economic growth and environmental sustainability in rural regions. In light of these considerations, the following first hypothesis was formulated for confirmation:

Hypothesis H1. *The implementation of digital technologies can significantly positively influence agricultural productivity at the EU country level.*

2.3. The Implications of Agricultural Digital Transformation

Digitalization in agriculture serves as a compelling tool for enhancing farmers' incomes by streamlining agricultural processes, boosting efficiency, and tapping into new markets via digital platforms. Consequently, research and policies focusing on these facets can play a pivotal role in alleviating rural poverty and fostering prosperity in agricultural communities [55–57]. Moreover, digitalization can facilitate the diversification of agricultural activities and pinpoint specific avenues for income growth across various agricultural sectors and regions [58–60]. This holistic approach can inform policy and investment endeavors aimed at maximizing the benefits of digitalization in agriculture and ensuring the balanced and sustainable development of rural areas [61].

Configuring appropriate policy, legal, and economic frameworks [62,63] is imperative to achieve sustainable digital transformation in agriculture. Attention should be directed toward designing socially responsible innovations to steer digitalization in agriculture [64]. Nonetheless, digital transformation is an ongoing process, and its future technological advancements and impacts remain uncertain. Its forthcoming configuration hinges on present interventions and governance measures, as well as societal and political discourses that shape perceptions and collective actions [63].

Enhancing farmers' information literacy and refining their technological skills are essential to empower them to effectively harness digital technologies and fully capitalize on the opportunities presented by digitalization in agriculture. By embracing and integrating new technologies, farmers can optimize their production processes, manage resources more efficiently, and enhance overall business performance. Cultivating heightened awareness of the significance of digitalization in agriculture can motivate farmers to invest in education and training to continually enhance their technological competencies [53]. This augmentation in farmers' digital capabilities can serve as a critical factor in augmenting income and fostering sustainable development in the agricultural sector [65].

Implementing efficient digital poverty alleviation management can yield numerous benefits. By leveraging digital information technology, cloud platforms, and data analysis, authorities can accurately pinpoint areas and populations affected by poverty and develop tailored strategies to help them overcome this plight [39]. A digital management system can enhance the efficacy of poverty alleviation fund utilization, ensuring that resources are allocated judiciously and beneficiaries receive timely support [66]. Such an approach can contribute to achieving poverty reduction targets and enhancing the quality of life for affected communities.

Furthermore, digitalization can unlock fresh opportunities for farmers, empowering them to manage their farms more effectively and make data-driven decisions [67]. This digital transformation can also enhance farmers' access to information and resources, particularly in rural or remote areas. Agricultural digitalization transcends the mere adoption of digital technologies; it signifies a profound overhaul of the entire agricultural sector. By integrating and leveraging these technologies efficiently, agriculture can become more productive, sustainable, and resilient to future challenges.

The integration of digital technology in agriculture significantly influences the advancement of high-quality agricultural practices, and further research endeavors could facilitate a deeper understanding of how the digital economy can effectively drive growth in agricultural output, agricultural gross value added, and agricultural productivity [68]. Examining the nexus between digital technologies and agricultural production is crucial in today's landscape, where modern agriculture increasingly relies on technological advancements to maintain competitiveness, sustainability, and efficiency. By probing into the relationships between digital technologies and agricultural production, we can enhance comprehension of how these technologies impact and enhance various aspects of agricultural operations. Consequently, this study formulated the following second hypothesis of the research for validation within the countries of the European Union:

Hypothesis H2. *European Union countries with a high degree of digitization have higher agricultural productivity than others with low digitization.*

3. Materials and Methods

3.1. Research Design

The research process began with conducting a comprehensive literature review to gather background information and insights. Based on the literature review, this paper proposes two hypotheses, focusing on analyzing the relationship between the use of digital technologies and agricultural productivity. Data were collected according to the research objectives and then processed and analyzed. The results obtained from the analysis are presented in this paper in a clear and organized manner. Following the presentation of results, discussions interpret the findings and expose their implications in the context of the research topic. Finally, this paper concludes by summarizing the essential research findings and highlighting their significance. Figure 1 illustrates the research process.

Based on the gaps identified during the literature review, research questions were formulated, serving as the basis for developing the hypotheses presented in the literature review section: How does the adoption of digital technologies impact agricultural productivity across EU countries? What are the significant associations between digital technology use and productivity related to the total labor force across EU countries?

3.2. Selected Data

Data were collected from the Eurostat database regarding the use of digital technologies in enterprises and relevant agricultural indicators to examine the relationship between digital technologies and agricultural efficacy across the European Union. This comprehensive dataset allows us to analyze how the adoption of digital technologies influences various aspects of agricultural performance within different EU member states. These data were compiled for every EU member state to examine the impact of digital technologies on agricultural productivity. Table 1 presents the indicators used for analyzing the relationships between digital technologies and agricultural outputs.

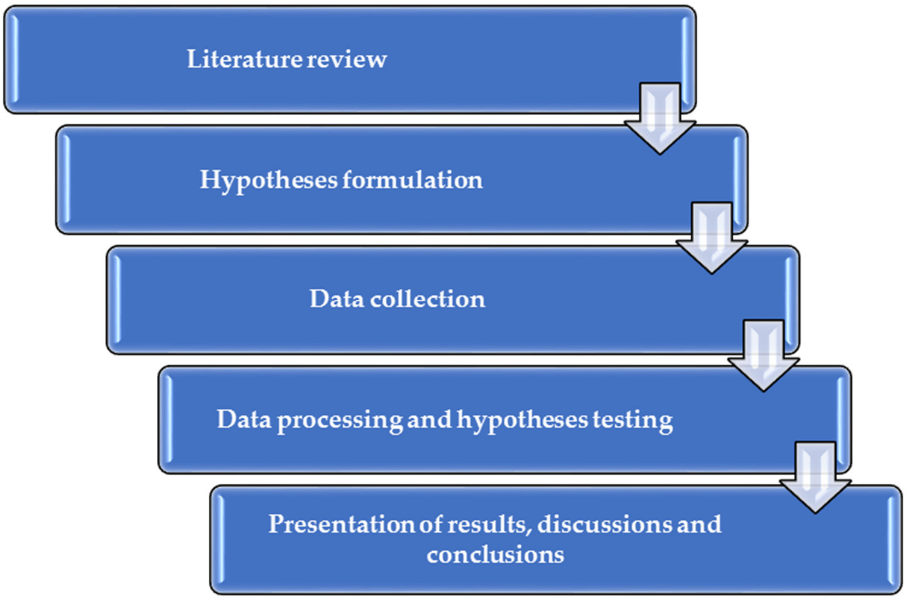

Figure 1. Research process stages. Source: developed by the author.

Table 1. Research variables.

Variable	Dataset	Measures	References
AI	Enterprises use AI technologies and perform data analytics	Percentage	[69]
CC	Buy cloud computing services used over the Internet	Percentage	[70]
BD	Analyze Big Data internally from any data source	Percentage	[71]
R	Use industrial or service robots	Percentage	[72]
IoT	Enterprises use IoT	Percentage	[73]
UAA	Utilized agricultural area	Hectare	[74]
AO	Agricultural output	Million purchasing power standards (PPS)	[75]
PRUA	Productivity related to the area used in agriculture	Million purchasing power standards (PPS)/hectare	[74,75]
LFI	Total labor force input	1000 annual work units	[76]
VAG	Gross value added at basic prices	Million euro	[77]
PRFI	Productivity related to the total labor force input	Euro/work units	[76,77]

Source: developed by the author based on [59–67].

The data for all indicators were collected from Eurostat, except for productivity related to the area used in agriculture (PRUA) and productivity related to the total labor force input (PRFI). These indicators were calculated based on the collected measures. The calculation formulas are as follows:

$$\mathrm{PRUA} = \frac{\mathrm{AO}}{\mathrm{UAA}} \tag{1}$$

UAA—utilized agricultural area;
AO—agricultural output;
PRUA—productivity related to the area used in agriculture.

$$\mathrm{PRFI} = \frac{\mathrm{VAG}}{\mathrm{LFI}} \tag{2}$$

LFI—total labor force input;
VAG—gross value added at basic prices;
PRFI—productivity related to the total labor force input.

This study aims to examine the impact of digital technology use on various types of agricultural productivity, particularly labor productivity, considering the effect of labor substitution with automated means. Many previous studies have utilized Total Factor Productivity as a measure of agricultural productivity. While Total Factor Productivity provides a comprehensive assessment by considering both labor and capital inputs, this study specifically focuses on labor productivity due to its relevance in the context of digital technology adoption. By examining labor productivity, this study aims to capture the direct impact of digital technologies on workforce efficiency, which is a crucial aspect given the increasing automation in agriculture.

Data regarding digital technologies target their implementation across the entire economy, not just within the agricultural sector. However, they serve as a robust indicator of each economy's propensity toward digital technology adoption, which can be considered in empirical research.

Table 2 presents descriptive statistical data characterizing the research variables used in structural equation modeling and cluster analysis.

Table 2. Descriptive statistics.

Variable	N	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
CC	27	17.50	78.30	46.7037	16.34714	0.020	−0.699
AI	27	1.00	13.00	5.7111	3.15867	0.836	−0.017
BD	27	2.70	28.70	12.3667	7.43686	0.743	−0.655
IoT	27	10.50	50.80	27.9037	9.63114	0.734	0.552
R	27	1.70	11.60	5.8630	2.44370	0.374	−0.057
PRUA	27	946.85	12,934.69	3223.7004	2937.86442	2.624	6.627
PRFI	27	7834.57	82,375.02	30,266.7678	21,501.74081	1.025	0.119

Source: developed by the author using SPSS v.27 based on [69–77].

3.3. Methods

This study used structural equation modeling to investigate Hypothesis H1. Agriculture is one of the fundamental pillars of the EU economy, and increasing agricultural productivity is essential for ensuring food security, enhancing competitiveness, and stimulating sustainable economic development in the region [56]. Implementing digital technologies in agriculture can enhance agricultural productivity [44].

Structural equation modeling (SEM) allows the investigation of complex relationships and interdependencies between variables involved in Hypothesis H1. This method can help understand how these variables influence each other and contribute to agricultural productivity [78,79]. SEM models can contribute to generalizing results and extending them to other contexts. By identifying significant patterns and relationships between the variables involved, these models can be applied in other regions or agricultural sectors, allowing for a more comprehensive understanding of the investigated phenomenon. This research uses a formative SEM model. In formative models, robustness is crucially important to ensure the reliability and validity of the results [78]. Various techniques can be employed to assess the robustness of the model, including bootstrapping. These methods help researchers evaluate the stability of the model estimates and test the sensitivity of the results to changes in the data or modeling assumptions. Furthermore, assessing multicollinearity and model fit indices, such as the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI), is essential to ensure that the model adequately captures the underlying relationships among variables. By employing these robustness checks, researchers can enhance the credibility and generalizability of their findings [78].

Previous studies [3,4,80–82] have demonstrated that SEM is a powerful and flexible method for analyzing the complex relationships among multiple and diverse variables affecting the agricultural sector. SEM allows researchers to model intricate interactions among observed and unobserved variables, making it well suited for testing and validating complex theoretical models, as emphasized by Garson [79] and Hair et al. [78]. Moreover, Kline [83] highlights that SEM is efficient in integrating and analyzing data from various sources. Therefore, the data collected from Eurostat, which provide comprehensive information on digital technology use and agricultural productivity in the EU, represent an ideal opportunity to apply SEM techniques. By using SEM within this context, the investigation can gain a deeper understanding of the multidimensional relationships among these variables and uncover insights that may inform sustainable agricultural policies and practices.

This study also uses artificial neural networks (ANNs) analysis to complement and validate the results obtained using the SEM model to ensure the robustness of the investigation. Other previous research has also demonstrated the utility of using ANNs in agricultural research. ANNs have been widely employed in various agricultural applications, including crop yield productivity prediction [84–86]. Studies have shown that ANN models can effectively capture the nonlinear relationships between input variables and agricultural productivity, thus providing valuable insights for decision-making in farming practices [86]. The ability of ANNs to handle multidimensional datasets makes it a powerful tool for analyzing agricultural systems and optimizing resource management strategies [87]. Through MLP, the ANN analysis can uncover hidden patterns and correlations within the data that traditional statistical methods may overlook, thus offering valuable insights for optimizing the integration of digital technologies in agriculture.

This paper used cluster analysis to investigate Hypothesis H2. This method can reveal significant differences between different clusters regarding the evolution of digital technologies and agricultural productivity, thus reflecting the diversity of contexts and agricultural strategies within the EU [56]. Cluster analysis plays a pivotal role in this context by offering a comprehensive view of the intricate interplay between digital technologies and agricultural performance across diverse regional landscapes within the EU [88–91]. This analytical approach empowers policymakers and stakeholders to customize interventions and allocate resources more efficiently to bolster agricultural productivity across various regions and agricultural systems within the EU [39,92]. Finally, investigating the relationships between digital technology measures and agricultural productivity through cluster analysis can provide valuable information for formulating agricultural policies at the EU level [93]. This information can guide strategic decisions regarding investments in digital technologies, thus supporting objectives of sustainable economic growth, agricultural efficiency, and food security within the European Union [17].

4. Results

4.1. Testing Hypothesis H1

The testing of Hypothesis H1 used structural equation modeling (SEM) in the partial least squares (PLS) variant. The software used was SmartPLS version 3.0. The model is formative, with the latent, endogenous variables being digital technologies, productivity per hectare, and work productivity in agriculture. The exogenous, observable variables of the model are CC, AI, BD, IoT, R, PRUA, and PRFI. Figure 2 depicts the empirical model used to test Hypothesis H1.

It is necessary to analyze the collinearity of variables to validate a formative SEM-PLS model [79]. VIF (Variance Inflation Factor) is a measure used in structural equation modeling (SEM) to assess the collinearity between independent variables. In SEM, collinearity can affect the stability of the model and the accuracy of parameter estimates. The VIF measures the extent to which the variation in an independent variable is explained by the other independent variables included in the model. A higher VIF indicates greater collinearity among the independent variables, which can lead to inaccurate parameter estimates and misinterpretation of results [78]. Monitoring VIF values in SEM analysis is essential to identify and correct collinearity issues. Generally, a VIF value lower than five is considered acceptable [79]. The VIF plays a crucial role in ensuring the quality and robustness of formative SEM models because by evaluating and managing collinearity using VIF in SEM analysis, researchers can ensure their models are reliable and their results are valid [79]. Table 3 presents the VIF for the formative SEM model.

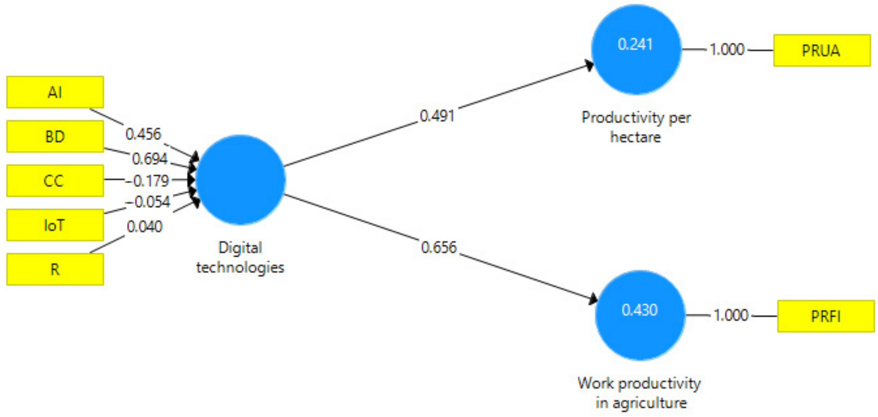

Figure 2. Empirical model. Source: developed by the author based on data using SmartPLS version 3.0.

Table 3. Multicollinearity.

	VIF
AI	4.023
BD	2.666
CC	1.795
IoT	1.402
R	1.956
PRFI	1.000
PRUA	1.000

Source: developed by the author based on data using SmartPLS v3.0.

In structural equation modeling (SEM), there are two essential indicators for assessing the quality and adequacy of the formative model: SRMR (Standardized Root Mean Square Residual) and NFI (Normed Fit Index) [79]. SRMR is a measure of the discrepancy between the observed covariance matrix and the estimated one in the SEM model. This statistic provides an assessment of the overall fit of the model, with lower values indicating a better fit of the model to the observed data. SRMR values below 0.08 are generally considered acceptable, although thresholds may vary depending on the research context [68]. In the case of the model analyzing the relationship between digital technology and agricultural productivity, SRMR has a value of 0.058. NFI is a model fit index that compares the value of the maximized likelihood function of the specified model with the value of the likelihood function of a base model (e.g., a null model). A higher NFI indicates a better fit of the model to the observed data. Generally, NFI values above 0.90 are considered acceptable to indicate a good fit of the model to the observed data [79]. In the case of the model analyzing the relationship between digital technology and agricultural productivity, NFI has a value of 0.927. These measures—SRMR and NFI—are essential for evaluating the quality and adequacy of the SEM model, indicating good reliability, validity, and fit of the studied SEM model.

Table 4 highlights the path coefficients established between latent variables by performing a basic bootstrapping procedure, with bias-corrected, two-tailed significance, and at a significance level of 0.05, using SmartPLS 3.0. This method allows for obtaining robust and reliable estimates of the relationships between latent variables within the analyzed model [78].

Table 4. Path coefficients.

	Original Sample	Sample Mean	Standard Deviation	T Statistics	*p*-Values
Digital technologies → productivity per hectare	0.491	0.489	0.321	1.531	0.126
Digital technologies → work productivity in agriculture	0.656	0.662	0.251	2.617	0.009

Source: developed by the author based on data using SmartPLS v.3.0.

The data presented in Table 4 reflect the path coefficients obtained in the SEM analysis for the relationship between digital technologies and productivity in agriculture. For the relationship between digital technologies and productivity per hectare, the path coefficient is 0.491. This value means there is a positive association between the use of digital technologies and productivity per hectare in agriculture, but this association is not statistically significant, given that the *p*-value is higher than the conventional significance level of 0.05. The lack of significant relationships between digital technology use and productivity per hectare can be attributed to the diverse agricultural landscapes across EU countries. Climate variations, soil conditions, and crop types differ significantly from one region to another, leading to varying levels of agricultural productivity. For instance, countries in Northern Europe may have different climate conditions and soil compositions compared to those in Southern Europe, impacting the effectiveness of digital technologies differently. Moreover, the types of crops cultivated in each country can also vary, further influencing the relationship between technology adoption and productivity. These geographical and agricultural differences highlight the complexity of assessing the impact of digital technologies on agricultural outcomes across the EU.

Regarding the relationship between digital technologies and labor productivity in agriculture, the path coefficient is 0.656. These findings reveal a favorable and statistically significant correlation between the adoption of digital technologies and workforce efficiency in agriculture, as evidenced by a *p*-value below 0.05.

Synthesizing the data presented in Table 4 highlights the substantial impact of digital technologies on labor productivity in agriculture. However, within the limits of this particular analysis, a significant correlation between digital technologies and productivity per hectare cannot be conclusively established. These outcomes underscore the significance and advantages of embracing digital technologies to enhance labor productivity within the agricultural sector, thereby partially validating Hypothesis H1.

To confirm the results obtained from applying the formative SEM model, we employed the Multilayer Perceptron (MLP) model within the artificial neural network (ANN) analysis. The MLP model provides a sophisticated approach to exploring the intricate relationships between variables. By employing MLP, the model can capture complex nonlinear patterns and interactions among various factors influencing agricultural productivity. This model allows for a more nuanced understanding of how different digital technologies interact with agricultural processes and contribute to productivity outcomes.

The input layer in the MLP model represents the degree of utilization of various digital technologies across the entire economy, while the output layer consists of the two dimensions of productivity: labor productivity and productivity per hectare. In the Multilayer Perceptron (MLP) model, the hidden layer represents the extent of digital technology use in agriculture. Both the input layer and the hidden layer in the MLP model employ Sigmoid activation functions, facilitating the transformation of input data into meaningful output. The overall average relative error, computed at 0.158, indicates the model's accuracy in predicting outcomes [87]. To ensure consistency and comparability, the input layer variables underwent normalization during the rescaling process. Figure 3 illustrates the complex relationships among the variables, providing valuable insights into the dynamics of the model.

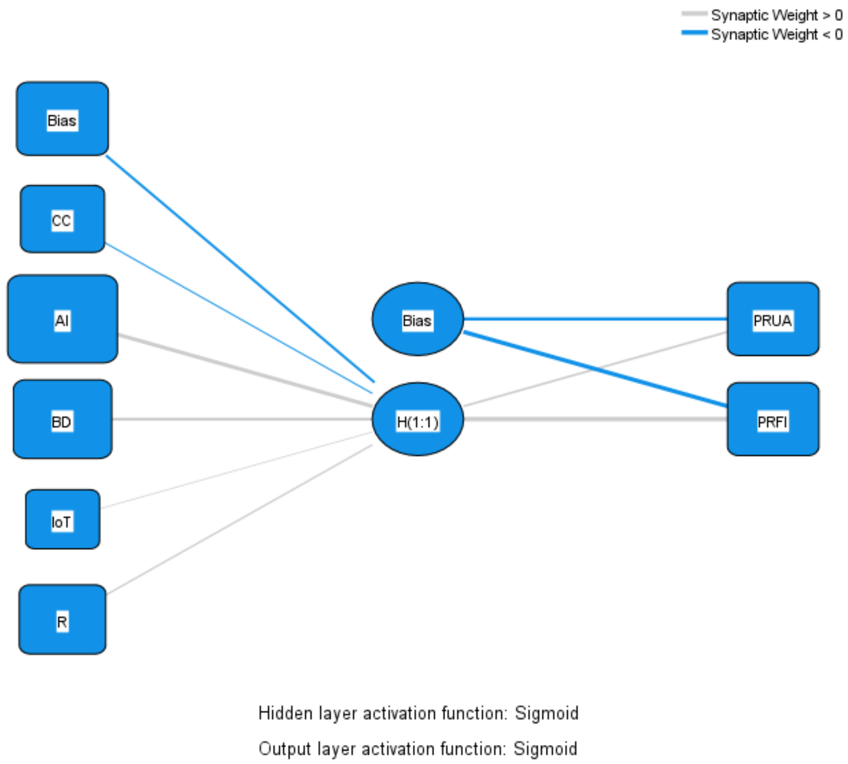

Figure 3. MLP model. developed by the author based on data using SPSS v.27.

Table 5 presents the predictors associated with both the input and hidden layer variables, elucidating the intricate relationships between them. It provides insights into how these predictors contribute to the overall model structure and functionality, offering a comprehensive understanding of the analysis conducted.

Table 5. MLP model predictors.

Predictor		Predicted Hidden Layer 1 H(1:1)	Output Layer PRUA	Output Layer PRFI	Importance	Normalized mportance
Input Layer	(Bias)	−1.358				
	CC	−1.022			0.123	29.2%
	AI	2.704			0.423	100.0%
	BD	1.826			0.292	68.9%
	IoT	0.064			0.008	2.0%
	R	1.076			0.154	36.3%
Hidden Layer 1	(Bias)		−1.991	−4.282		
	H(1:1)		1.083	5.621		

Source: developed by the author based on data using SPSS v.27.

The results of the MLP model indicate that the use of digital technologies, such as artificial intelligence, Big Data, robots, and IoT, has a positive impact on productivity in agriculture, both in terms of productivity per hectare and particularly labor productivity, contributing to greater efficiency and sustainability of agricultural processes. The bias of the hidden layer for PRFI has a smaller magnitude compared to the influence of the main variable. However, the bias is significant, indicating other essential influences on labor productivity. The bias of the hidden layer for PRUA has a higher magnitude compared to the influence of the main variable. The results of the MLP model confirm the findings of the SEM model, highlighting the substantial impact of digital technologies on labor productivity in agriculture, thus validating Hypothesis H2.

4.2. Testing Hypothesis H2

Although the association between digital technologies and labor productivity is evident in this study, several factors can influence it. For example, the level of accessibility to digital technologies, the technical capabilities of farmers, and the digital infrastructure available in agricultural areas can play a significant role in how digital technologies are adopted and used in agricultural practices. Therefore, this paper further investigates, using cluster analysis, how EU countries group into homogeneous clusters based on digital technology values and levels of agricultural productivity. The optimal approach was the Ward linkage method [94]. Figure 4 presents the dendrogram resulting from the cluster analysis.

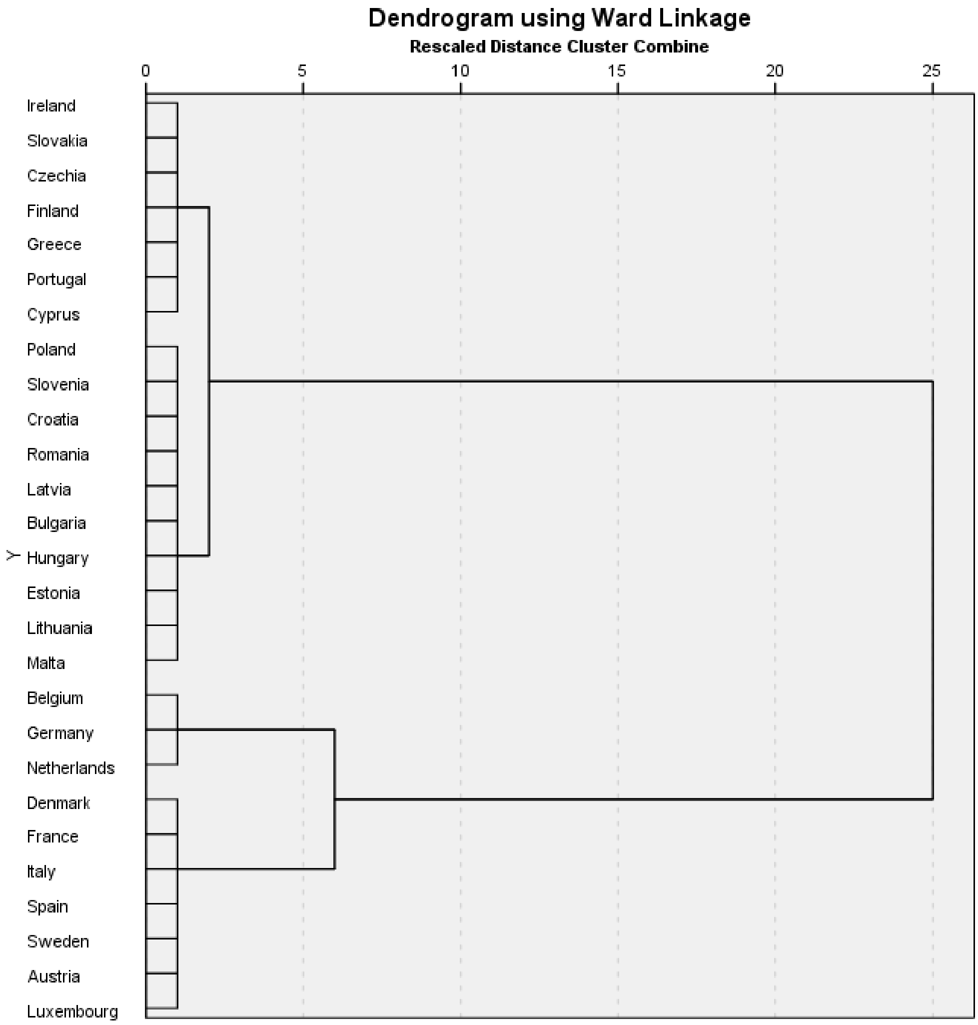

Figure 4. Dendrogram. Source: developed by the author based on data using SPSS v.27.

From the analysis of Figure 4, one can observe the existence of four relatively homogeneous clusters formed by EU countries. Table 6 depicts the four clusters based on the values of digital technologies and levels of agricultural productivity.

Table 6. Hierarchical clusters.

	CC	AI	BD	IoT	R	PRUA	PRFI
Belgium	51.70	10.50	21.90	28.20	10.20	6066.40	74,271.86
Germany	47.00	7.60	16.60	35.60	5.20	2960.54	66,880.26
Netherlands	61.20	10.70	25.90	20.70	6.20	12,121.48	82,375.02
Cluster A mean	53.30	9.60	21.47	28.17	7.20	5065.00	59,636.15
Denmark	69.50	13.00	23.70	20.00	11.60	2867.22	57,050.42
France	26.80	4.00	19.50	22.00	7.30	2150.11	55,906.98
Italy	61.40	3.00	7.40	32.30	8.70	3415.27	40,245.65
Spain	30.00	6.60	6.50	27.50	8.60	1879.31	40,767.07
Sweden	71.60	7.90	13.00	40.30	6.80	1436.94	39,047.59
Austria	46.50	6.00	7.00	50.80	5.40	2314.62	36,575.91
Luxembourg	37.00	8.20	16.80	22.20	4.60	2283.49	47,395.89
Cluster B mean	48.97	6.96	13.41	30.73	7.57	2335.28	45,284.21
Ireland	63.10	5.30	22.40	34.00	3.50	1516.48	23,996.75
Slovakia	34.40	5.10	4.60	27.40	6.70	1646.93	23,566.08
Czechia	47.20	3.90	9.10	31.40	5.90	1872.82	24,915.47
Finland	78.30	12.20	19.20	40.50	8.90	1162.26	28,541.14
Greece	23.60	2.70	12.20	22.80	1.90	3265.02	22,069.77
Portugal	37.50	5.40	10.20	23.10	7.60	2423.25	20,437.14
Cyprus	52.90	3.40	2.70	33.30	1.70	5862.16	18,735.21
Cluster C mean	48.14	5.43	11.49	30.36	5.17	2535.56	23,180.22
Poland	55.70	2.80	7.90	18.60	4.30	2714.68	8530.87
Slovenia	40.20	5.70	5.10	49.50	6.60	2636.19	7834.57
Croatia	45.10	5.80	13.00	23.20	4.30	2925.95	9742.79
Romania	18.40	1.00	4.30	10.50	2.50	2425.13	10,463.40
Latvia	35.80	3.70	7.40	28.40	5.10	946.85	9276.99
Bulgaria	17.50	2.20	5.70	15.00	3.30	1612.46	14,706.35
Hungary	44.90	2.80	6.40	22.30	3.80	2683.19	14,809.40
Estonia	58.60	2.90	8.00	17.40	5.60	1315.49	16,154.92
Lithuania	38.40	3.80	8.70	28.40	4.80	1600.98	12,647.29
Malta	66.70	8.00	28.70	28.00	7.20	12,934.69	10,257.94
Cluster D mean	42.13	3.87	9.52	24.13	4.75	3179.56	11,442.45
UE mean	46.70	5.71	12.37	27.90	5.86	3223.70	30,266.77

Source: developed by the author based on data using SPSS v.27.

Figure 5 illustrates the composition of the four clusters.

Cluster A comprises countries with a remarkably high level of digitalization and notable productivity performance, both per hectare and per labor force, exceeding the EU mean by a considerable margin. This cluster includes countries such as Belgium, Germany, and the Netherlands, which are recognized for their substantial commitment to digital innovations and their adept utilization of these innovations to enhance economic effectiveness and output. Notably, the Netherlands stands out as an exemplary case—a nation seamlessly integrating intensive agricultural practices with extensive digital technology implementation across economic and societal domains. Renowned for its technological advancements and sophisticated agricultural practices, such as greenhouse utilization, efficient irrigation systems, and crop monitoring technologies, the Netherlands has emerged as a global leader in agricultural and food product exports despite its limited natural resources.

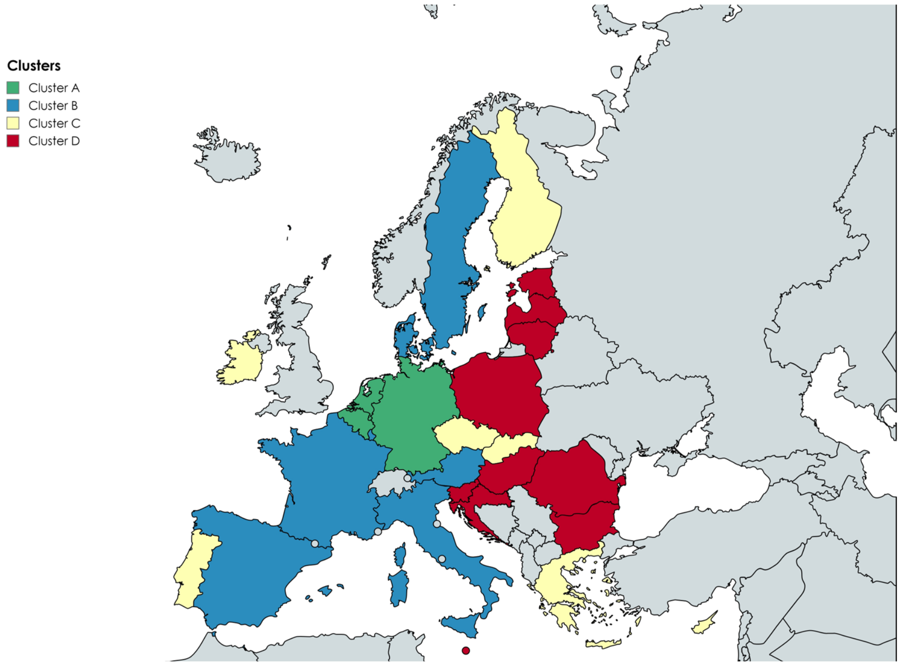

Figure 5. The distribution of countries across clusters. Source: developed by the author based on collected data from Eurostat using MapChart. https://www.mapchart.net/ (accessed on 16 March 2024).

The second cluster encompasses countries with a high degree of digitalization and commendable productivity performance, particularly in terms of labor force productivity, significantly surpassing the EU average. Notable countries in this cluster include France, Denmark, Luxembourg, and Italy. France stands out for its investments in digital infrastructure and ongoing efforts to foster technological innovation, consistently demonstrating labor productivity levels exceeding the EU average. Denmark, recognized for its innovation and rapid adoption of digital technologies, boasts one of the world's most productive economies, attributed to investments in education, research, development, and robust digital infrastructure. Luxembourg, among the wealthiest and most digitized EU member states, exhibits remarkable economic efficiency and technological advancement, achieving notable labor productivity in agriculture owing to its skilled workforce and adaptability. Italy, renowned for its innovation and manufacturing heritage, is witnessing a burgeoning digital industry, leveraging digital technologies to enhance economic performance despite facing efficiency and competitiveness challenges, remaining a significant European economy.

Clusters C and D encompass countries with lower levels of digitalization compared to the EU average and significantly lower agricultural productivity levels. Cluster D exhibits the lowest levels of labor productivity and digital technology implementation in the economy.

Cluster analysis validates Hypothesis H2, indicating that European Union countries with high digitalization levels demonstrate superior agricultural productivity compared to those with low levels of digitization. This finding underscores the importance of investing in technology and digitalization to enhance agricultural sector performance.

5. Discussion

The influence of the digital economy on enhancing high-quality agriculture has garnered considerable attention amidst the ongoing digital transformation of the agricultural sector [95]. This shift toward digitalization has prompted extensive discussions and investigations into how digital technologies can revolutionize agricultural practices and enhance the overall quality of agricultural products. The digital economy has bridged the information gap between producers and consumers, enabling producers to customize agricultural products to meet consumer demand [13]. The progression toward eco-friendly agriculture is an inevitable imperative for agricultural modernization.

The digital economy has emerged as a catalyst for innovation in Total Factor Productivity, exerting a positive impact on the agricultural sector [96,97]. The adoption of digital technologies in agriculture can fundamentally change how agricultural resources are managed, leading to increased efficiency and environmental sustainability [98,99]. Agricultural digitalization has become a critical factor in the development of high-quality agriculture [97].

The literature on technological innovation is extensive and spans various fields, including economics, sociology, and psychology. These studies highlight the social role of technology, its emergence, dissemination, adoption by actors, anticipated impacts, and other aspects [100]. Market developments, policies, and institutional structures are considered factors that either promote or hinder technological development, diffusion, and adoption [101]. Generally, these theoretical perspectives emphasize the role of multiple actors and mechanisms of distributed learning in technological changes, focusing on inter-organizational networks where innovation flourishes.

Our findings indicate that the utilization of digital technologies has a significant impact on labor productivity in agriculture, supporting Hypothesis H1, which suggests that implementing these technologies can positively influence agricultural productivity at the EU level. Through the use of digital tools such as IoT (agricultural sensors), AI-based crop monitoring systems, Big Data, cloud computing, and automated agricultural processes using agricultural robots, farmers can enhance efficiency and achieve higher yields from available resources. The results obtained from investigating the validity of Hypothesis H1 through SEM are further validated by neural network analysis.

Additionally, our results corroborate the findings of Klerkx et al. [19,102], who introduced the concept of digital agricultural practices and analyzed their effect on agricultural productivity through case studies of digital agricultural companies in Turkey, and Zhang and Fan [53], who conducted an empirical study involving thousands of farmers in China regarding agricultural digital transformation. These analyses contribute to identifying the benefits and challenges associated with adopting digital technology in agriculture and developing appropriate strategies and policies to promote more efficient and sustainable agriculture. The impact of digitization on enhancing agricultural productivity is also evident in refining external market conditions and enhancing agricultural regulations [103].

The development of digital agriculture has the potential to completely transform how agriculture is practiced and managed [44,45,88]. The use of digital technologies in agriculture can contribute to increased efficiency and productivity, reduced resource use and environmental impact, and improved quality of agricultural products [104]. By implementing digital agricultural practices, farmers can access information and tools to support their decisions and optimize agricultural processes, thus contributing to sustainable agriculture.

The digitization of agriculture encompasses the fusion of digital innovations like artificial intelligence, Big Data, and robotics, and these digital advancements are linked to agricultural production setups via the Internet of Things [31,67,105]. Within this evolving landscape, it is crucial to underscore that digitalization is not solely an escalating pattern but also an imperative for agriculture in the 21st century. The continuous improvement in digital technologies can contribute to increasing agricultural productivity, optimizing resource use, and adapting to market requirements. These innovations can enhance agricultural resilience to climate change and other environmental threats.

This study's outcomes align with Deichmann et al.'s findings [27], advocating for the integration of technologies like Big Data, cloud computing, and mobile communications in agriculture, which can significantly boost operational efficiency and sustainable development. These technologies not only enhance production and resource management but also foster transparency and public involvement in governmental decision-making and policy execution. Through the analysis of Big Data, governments and organizations can better grasp farmers' needs, tailor policies accordingly, and ensure local adaptability. Moreover, the adoption of blockchain technologies can enhance food supply chain traceability and certification, ensuring food safety and product quality. Consequently, investments in agricultural digitization are pivotal for sustainable economic growth and enhancement of the quality of life in rural areas.

The development and deployment of intelligent digital services in agriculture offer substantial opportunities for enhancing efficiency, productivity, and sustainability in the sector. These services encompass applications for data analysis, crop monitoring systems, weather forecasting technologies, and resource management tools. By leveraging these advanced technologies, farmers can make well-informed decisions, optimize natural resource utilization, reduce environmental footprints, and enhance agricultural business profitability.

Following the examination of Hypothesis H2, cluster analysis unveiled that European Union countries with high digitalization levels exhibit greater agricultural productivity, affirming the correlation between digitalization and agricultural performance. Cluster analysis serves as valuable guidance for policymaking and strategy formulation at the EU and national levels to bolster digitalization and agricultural performance growth across the region. This cluster analysis is crucial as it highlights examples of best practices from countries with high levels of digitalization and agricultural productivity. By identifying these practices, other countries with lower agricultural productivity and lower levels of digitalization can improve their performance and increase their competitiveness by adopting and adapting these successful models. Through benchmarking, countries with lower agricultural performance can learn from the experience and strategies of leading countries, identify improvement opportunities, and implement appropriate solutions in their contexts. Thus, cluster analysis becomes not only a performance evaluation tool but also a guiding and continuous improvement tool in the agricultural sector of the European Union.

The findings regarding Hypothesis H2 align with the existing literature, underscoring the positive impact of digitalization on farmers' incomes and rural poverty reduction [55–60]. Tokgoz et al. [55] and Ehlers et al. [56] highlight the potential of digital agriculture to enhance efficiency and access new markets through digital platforms. Establishing appropriate policy and legal frameworks is crucial to facilitating a sustainable digital transition in agriculture [62,63]. By promoting socially responsible innovations and policies that ensure equitable access to digital technologies, the benefits of digitization can be evenly distributed, fostering sustainable growth in rural areas across the EU. Leveraging digital information technology, governing bodies can optimize the effectiveness of European funds allocated for poverty alleviation and ensure efficient resource allocation. Policies and government interventions should focus on creating a conducive environment for the adoption and effective utilization of digital technologies in agriculture, maximizing the benefits of digitization, and promoting sustainable development in rural regions [44].

The digital technologies used across the entire agricultural value chain can significantly enhance efficiency, sustainability, and competitiveness in the agricultural sector [42]. Automating agricultural processes can reduce reliance on human labor and optimize resource utilization. Therefore, the digital transformation of agriculture not only meets efficiency and sustainability goals but can also bring significant economic benefits and contribute to increased rural prosperity and overall economic development [43].

Digitization can reduce costs for farms and the environmental impact of agricultural production while improving crop yields, farmer incomes, and the provision of even safer and higher-quality food [64]. Despite the evident benefits brought by digitization, there are also concerns regarding potential inequalities and risks associated with this transformation [17]. Thus, there is a risk that farmers in low-income countries may be marginalized or lack access to advanced digital technologies, perpetuating cycles of poverty and inequality. Moreover, the increasing dependence of farms on high-tech companies could heighten their vulnerability to market changes or corporate policies that are not always farmer- or agricultural community-oriented [16].

With the implementation of digital solutions in agriculture for environmental protection, new opportunities arise for more efficient monitoring and management of natural resources [106]. Digital technologies, such as IoT sensors and real-time data analysis, can help farmers closely monitor soil quality and use water and fertilizers more efficiently, thereby reducing the negative impact on the surrounding environment [107]. The implementation of digital solutions in agriculture can contribute to enhancing environmental sustainability by reducing the use of pesticides and other harmful chemicals, thus protecting biodiversity and the natural habitat of species [108]. By optimizing the production process and efficiently managing resources, digitization can contribute to environmental conservation and reduce the negative impact of agriculture on fragile ecosystems.

The integration of digital technologies in agriculture can also facilitate access to agricultural information and services for farmers in rural areas and connect them to more extensive and more competitive markets [109,110]. This broad access can help reduce the digital divide between urban and rural areas and improve the living standards of agricultural communities [111].

Despite its benefits, digital transformation also presents various challenges and perceived unintended consequences. These include unequal access to the Internet and digital technologies, the potential for farmers to become overly reliant on technology, and the erosion of traditional agricultural knowledge. Furthermore, establishing a practical governance framework for this transformation is challenging due to the rapid pace of technological change and the involvement of diverse stakeholders [106,112].

In essence, there is an urgent need for an appropriate governance approach to ensure that digitalization proceeds in a socially responsible manner. While policymakers anticipate positive outcomes, it is also essential to adopt a critical perspective. One of the primary challenges in crafting policy measures is the high level of uncertainty surrounding the impacts and future trajectory of digitalization. Therefore, an adaptive and dynamic governance approach is essential to navigate these unknowns and uncertainties [33].

5.1. Theoretical Implications

Digitalization is utilized to achieve the deep integration of the digital economy and agriculture, to bolster support for innovative elements in the digital transformation of agriculture, to drive the enhancement of the agricultural framework with Big Data as a central production component, to initiate fundamental shifts in digital agricultural production and practices, and to provide a reference point for research and decision-making in the sustainable management of agriculture.

Through digitalization, the comprehensive integration of the digital economy into all facets of agriculture, spanning production processes, resource management, and marketing, is pursued. One of the major priorities is to stimulate innovation in the agricultural sector through digital technologies. This fact involves encouraging research and development in areas such as artificial intelligence, Big Data, cloud computing, robots, and the Internet of Things to create innovative digital solutions tailored to the specific needs of farmers and the agricultural supply chain. Digital transformation of agriculture optimizes production processes, leading to increased efficiency and competitiveness across the entire sector. The benefits of the digital revolution must be equitably distributed and accessible to all participants in the agricultural sector.

The democratization of digital technologies aims to level the playing field and promote inclusivity within the agricultural industry, fostering innovation, sustainability, and economic growth. Essentially, the digital transformation of agriculture is not just a process of technological modernization but also an opportunity to improve the management of resources, decision-making, and sustainability throughout the agricultural value chain. By adopting an integrated and innovation-oriented approach, it is believed that digital transformation will significantly contribute to the modernization and sustainable development of agriculture in the 21st century.

5.2. Empirical Implications

Digital technology in agriculture has the potential to enhance the efficiency of agricultural practices, consequently fostering economic advancement while concurrently preserving the environment. Exploring the correlation between the digital economy and agricultural productivity stands as a pivotal area of study in advancing contemporary and sustainable agricultural practices. This digital revolution within agriculture not only presents novel prospects for farmers and agricultural entities but also streamlines access to cutting-edge technologies and global markets through digital platforms.

This paper highlights, using structural equation modeling and artificial neural network analysis, that the integration of digital technologies in agriculture holds promise for heightened productivity. By embracing digital agricultural methodologies, farmers gain access to invaluable information and tools to bolster their decision-making processes and modernize agricultural operations, thereby contributing to the realization of sustainable agricultural practices.

The application of cluster analysis within the framework of digitalization and agricultural productivity not only affirms the nexus between these two elements but also furnishes indispensable insights to steer policies and investments toward augmenting the efficacy and competitiveness of the agricultural sector within the European Union. Policymakers and stakeholders can use these findings to develop tailored strategies designed to promote the extensive integration of digital technologies in agriculture, thereby enhancing productivity, resilience, and sustainability across diverse agricultural systems within the EU. These strategies may include incentives, support programs, and regulatory frameworks aimed at facilitating the adoption and effective use of digital solutions by farmers and agricultural enterprises. Collaboration between government agencies, research institutions, industry partners, and farmers' associations can further drive innovation and technology transfer in agriculture, leading to long-term benefits for the sector and the broader economy.

6. Conclusions and Policy Recommendations

The integration of digital technologies into business processes has not only optimized operations but has also spurred innovation and growth across various industries. This paper's findings highlight the potential for digital technology integration to enhance agricultural productivity and competitiveness, facilitating adaptation to evolving business landscapes. The research results of this paper have shown that the integration of digital technologies into business can help increase agricultural productivity and market competitiveness and help businesses adapt to the requirements and changes in the business environment.

By embracing advanced digital tools, farmers can access crucial information for informed decision-making, fostering innovation and efficiency in agriculture. Digital platforms and innovation ecosystems offer avenues for farmers to adopt cutting-edge technologies, leading to improved productivity and economic sustainability. Moreover, digitalization can bridge the digital gap, providing farmers in rural areas access to resources and markets, thus promoting inclusion and prosperity. These technologies can enhance efficiency and productivity in agriculture, leading to increased incomes and economic sustainability for farmers. Digitalization can contribute to reducing the digital divide and improving access to information and resources for farmers in rural areas, including smallholder farmers and marginalized communities.

However, this study is subject to limitations. While robust analytical frameworks like structural equation modeling, artificial neural network analysis, and cluster analysis offer insights into digital technology's impact on agriculture, their sensitivity to variable and model selection should be highlighted. Moreover, this study's cross-sectional nature may overlook long-term trends in digital technology adoption and agricultural productivity.

Also, the analysis primarily focused on overall indicators of digital technology use due to the lack of data for the considered technologies—AI, CC, BD, R, and IoT used in agriculture across EU countries. Future research should explore the enduring implications of digital technology integration in agriculture, considering socioeconomic and agricultural contexts. Strategies for widespread adoption of digital technologies in agriculture should be tailored to each EU member state's unique requirements. Longitudinal studies can provide deeper insights into the evolving relationship between digital technologies and agricultural productivity.

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