agriculture

Article

Assessing Farm-Level Digital Maturity in European Agriculture: The Digital Farm Index and Investment Barriers to Agriculture 4.0

Claudiu-Ovidiu Ailioaei, Constantin-Dragos Dumitras, Oana Coca * and Gavril Stefan

Faculty of Agriculture, Agroeconomy Department, "Ion Ionescu de la Brad" Iasi University of Life Sciences, Mihail Sadoveanu Alley 3, 700490 Iasi, Romania; claudiu.ailioaei@iuls.ro (C.-O.A.); dragos.dumitras@iuls.ro (C.-D.D.); gavril.stefan@iuls.ro (G.S.)

* Correspondence: oana.coca@iuls.ro

Abstract

The transition toward Agriculture 4.0 aims to improve farm performance and sustainability; however, existing macroeconomic indicators do not fully capture the depth of farm-level digital adoption. This study proposes the Digital Farm Index (DFI) as a tool for assessing digital maturity and regional disparities in European agriculture. The research combines bibliometric mapping of the scientific literature with an empirical DFI assessment for 18 European Union Member States using Eurostat data. The empirical assessment utilizes multiple linear regression, log-linear scale modeling, and hierarchical clustering to analyze adoption patterns and structural determinants. The index integrates four dimensions: connectivity, precision agriculture, robotics, and farm management information systems (FMIS). Results indicate that adoption is concentrated in larger farms, as area-weighted digital maturity (DFI-Hectares) consistently exceeds farm-level adoption (DFI-Farms). CAPEX-based cost modeling suggests the existence of a technological indivisibility threshold, whereby digitalization may become an entry barrier for fragmented farms with limited economies of scale. Multiple linear regression suggests an East–West structural trend: while farm size influences the territorial diffusion of technology, a more consolidated regional innovation ecosystem appears more relevant for farm-level adoption. Findings also highlight a hardware–software imbalance and limited use of data-driven managerial tools. Support policies should therefore move beyond equipment subsidies and include technology transfer networks, digital skills, and managerial data-integration tools.

Keywords: Digital Farm Index (DFI); Agriculture 4.0; cost of digitalization; farm performance

Academic Editors: Claudio Bellia and Christos Karelakis

Received: 26 May 2026
Revised: 22 June 2026
Accepted: 20 July 2026
Published: 22 July 2026

1. Introduction

Global agriculture is currently undergoing a critical phase, characterized by the convergence of unprecedented systemic pressures. On the one hand, accelerated demographic growth toward an estimated population of 9.7 billion [1] will necessitate a 35% to 56% increase in global food demand by the year 2050 [2]. On the other hand, the productive capacity of ecosystems is constrained by the progressive degradation of soil and water resources [3], biodiversity decline [4], and, critically, the intensification of climate variability. Recent IPCC reports confirm an increasing frequency of extreme weather events, such as droughts and floods, which destabilize agricultural yields and threaten global food security [5,6].

 https://doi.org/10.3390/agriculture16141565

In response to these existential challenges, the agricultural sector is undergoing a technological paradigm shift, conceptualized in the literature as "Agriculture 4.0" or "Smart Farming" [7]. This fourth agricultural revolution marks the transition from mechanization and genetic breeding to a knowledge-intensive agriculture, based on data and digital interconnectivity [8]. Unlike previous stages, the current technological ecosystem integrates solutions such as the Internet of Things (IoT) for real-time monitoring [9], Big Data analytics for predictive modeling [10], Blockchain technology for traceability [11], and cyber-physical systems (CPS) that enable process automation through robotics and artificial intelligence [12,13]. Beyond environmental mitigation, digital adoption offers profound microeconomic and operational benefits for farmers. Technologies such as automated steering, IoT sensors, and Farm Management Information Systems (FMIS) optimize labor efficiency, improve real-time agronomic risk management, and significantly reduce input costs, thereby securing long-term farm profitability and operational resilience [14,15].

At the European Union level, digitalization is no longer an option but a strategic necessity embedded in the European regulatory framework. The "European Green Deal" and the "Farm to Fork" strategy establish ambitious sustainability targets for the 2030 horizon, including a 50% reduction in pesticide use and a 20% reduction in fertilizers [16,17]. The academic literature highlights that achieving these objectives without compromising productivity is unlikely in the absence of precision agriculture technologies [18]. Variable Rate Technologies (VRT) and GNSS guidance systems have demonstrated the capacity to reduce chemical inputs by 10–30%, while maintaining or even improving farm gross margins [14,19,20]. This is also consistent with previous research showing that agricultural performance across the European Union is shaped by a complex interaction of structural, economic, and technological determinants [21]. Simultaneously, digitalization is becoming an essential facilitator for accessing eco-schemes under the 2023–2027 Common Agricultural Policy, which links payment disbursement to the demonstration of digitally monitored environmental performance [22,23].

However, the diffusion of innovation among European farmers remains heterogeneous and fragmented [24]. The literature identifies multiple barriers, ranging from high investment costs and a lack of standard interoperability [25] to the digital skills gap [26,27]. A systemic barrier, insufficiently explored, is "technological indivisibility," which implies a minimum investment threshold relatively independent of the production scale [28,29]. This characteristic generates the risk of technological asymmetry within the agricultural sector between large farms, capable of amortizing fixed costs (CAPEX), and small-scale holdings, for which digitalization becomes economically unsustainable [29,30].

In this context, general macroeconomic indicators such as the Digital Economy and Society Index (DESI), while useful at the national level, cannot fully capture the reality of digital adoption within farms. These indicators focus on communication infrastructure and basic digital skills of the population, but do not capture the specifics of agricultural technologies. On the other hand, current tools in the literature measuring technological readiness are often purely qualitative or evaluate technologies in isolation. Furthermore, many studies focus on return on investment (ex-post), leaving a gap in understanding initial financial barriers (CAPEX) and how these costs burden each cultivated hectare. Therefore, the scientific novelty of the proposed Digital Farm Index (DFI) lies in its capacity to offer a much more practical picture connected to economic reality, differentiating itself from existing indicators through three essential aspects: (1) A farm-level perspective: Instead of providing a generic national digital score, the DFI measures technology adoption directly in the field. Through its dual evaluation (DFI-Farms and DFI-Hectares), the index shows exactly how technology is distributed across farm types and actual areas. (2) An integrated approach (hardware and software): The DFI is designed to capture the hardware-software paradox [31,32]. The index demonstrates that digitalization does not merely mean purchasing modern physical machinery (Robotics, Precision Agriculture) and connecting them to a network but also integrating and utilizing data through a centralized managerial system (FMIS). (3) Connection to financial reality: The DFI does not function as a simple technology checklist. It was designed to correlate directly with initial acquisition costs (CAPEX), allowing digitalization to be analyzed as a strict investment decision, conditioned by the farm's budget and physical size.

The scientific novelty of this research lies in its dual methodological architecture, which connects the theoretical dynamics of the literature with the empirical economic reality of farm digitalization. The paper introduces the Digital Farm Index (DFI) and proposes a cost assessment model based on real market data, allowing for the measurement of minimum investment thresholds (CAPEX) at the microeconomic level. The major theoretical contribution consists of reinterpreting agricultural digitalization as an investment marked by technological indivisibility and the predominance of fixed costs.

Theoretically, this study builds on the Diffusion of Innovations framework [33] and the theory of economies of scale [29]. The study contributes to existing literature by treating digital adoption not simply as a technological upgrade, but as a scale-dependent capital investment. By applying the concept of 'technological indivisibility' to Agriculture 4.0, our research shifts the focus from traditional profitability calculations to the initial financial barriers (CAPEX) that restrict smaller, fragmented farms.

The objective of this research is twofold: (i) to map the evolution of scientific interest through bibliometric techniques and (ii) to evaluate the digital maturity and investment costs (€/ha) across 18 European Union Member States. To this end, the study tests the hypothesis that economies of scale and technological indivisibility represent key determinants of digital adoption. Furthermore, the research explicitly aims to explore the potential East–West structural disparities across the 18 Member States for which harmonized Eurostat data on commercial farms were available. This regional comparison is critical due to distinct historical trajectories: Western European agricultural systems are traditionally highly capitalized and structurally consolidated, whereas Eastern European agriculture continues to grapple with severe land fragmentation and lower investment capacity following the post-socialist transition.

Through this integration, the present study overcomes the limitations of existing macroeconomic indicators and provides a detailed perspective on how land fragmentation and the lack of support networks shape the new geography of digital inequality in European agriculture.

2. Materials and Methods

The study aims to assess the digital maturity of European agriculture and estimate the capital expenditure (CAPEX) thresholds associated with the transition to Agriculture 4.0. The methodological framework adopts a sequential explanatory mixed-methods design, integrating quantitative analysis of the scientific literature with econometric modeling of statistical data. This dual architecture allows for triangulation of results by correlating theoretical trends identified in the literature with the empirical reality of agricultural holdings [34].

The empirical component focuses on the segment of commercial farms defined by standard output (Standard Output > €100,000). This selection is justified by the decisive role of these farms in ensuring European food security and by their superior capacity to absorb innovation, according to theories of technological diffusion [33]. The comparative sample includes 18 European Union Member States (Austria, Belgium, Czechia, Cyprus, Croatia, Estonia, Finland, France, Germany, Greece, Ireland, Latvia, Portugal, Romania, Slovakia, Sweden, the Netherlands, Hungary), for which the Eurostat datasets used provide complete and comparable information for the reference year.

Based on a comprehensive review of the theoretical framework regarding technology adoption and structural agricultural economics, four working hypotheses were formulated:

H1 (Regional Disparities): *Drawing from existing literature that documents structural disparities and the global divide in digital agriculture [23,30,35], we hypothesize that the level of digital maturity of farms, as measured by the DFI, differs significantly between Member States in the western and eastern parts of the European Union.*

H2 (Economies of scale): *In accordance with the microeconomic theory of economies of scale [29], there is a significant inverse relationship between the average size of commercial farms and capital expenditure (CAPEX) per hectare, indicating that digitalization becomes more economically feasible as fixed costs are spread over larger areas [29].*

H3 (Hardware-Software Paradox): *Based on recent studies highlighting the gap between physical equipment acquisition and data-driven management [31,32,36], adoption rates for tangible technologies, such as precision agriculture and robotics, are higher than those for intangible solutions, such as FMIS, reflecting insufficient use of data in decision-making at the farm level [31,32].*

H4 (Entry barrier): *In line with research on the economics of adoption and financial constraints in agriculture [20,37], the minimum investment threshold (CAPEX) represents a structural entry barrier, and cost-efficiency investment scenarios are more accessible to large-scale farms than to fragmented ones.*

2.1. Data Collection and Processing

The bibliographic data selection process followed the standardized PRISMA 2020 protocol to ensure the transparency and reproducibility of the analysis [38]. To ensure scientific rigor, the entire methodological framework was designed to allow for full replicability based on an explicit bibliometric query, harmonized Eurostat indicator sets, and standardized calculation equations.

The systematic literature selection was structured into three explicit PRISMA stages. During the Identification stage, data on the dynamics of scientific interest were extracted from the Web of Science Core Collection (WoS) database [39]. The query was performed on 22 January 2026, applying a Boolean search string to the Topic field (TS = Title, Abstract, Author Keywords, Keywords Plus), targeting the intersection between technological terms (e.g., "IoT," "artificial intelligence") and economic terms (e.g., "productivity," "ROI"). In the Screening stage, the search included all indexes associated with the WoS Core Collection but was restricted via automated filters exclusively to "Article" and "Review" document types published in English between 2000 and 2025, to guarantee scientific quality. Finally, during the Eligibility stage, a manual screening of titles and abstracts was conducted to exclude duplicates and out-of-scope papers (e.g., purely computational studies lacking an agricultural context), resulting in a refined final sample of 3,500 documents.

Indicators on digitalization and farm structure were extracted from the Eurostat database using the harmonized datasets ef_m_farmleg and ef_mp_digi [40]. To estimate capital expenditures (CAPEX), data were obtained by triangulating information from the AFIR reference price database [41] with validated catalogs from technology suppliers. Monetary values were indexed to the year 2026 using the Industrial Producer Price Index (IPPI) to accurately reflect recent industrial inflation [42].

2.2. Construction of the DFI Index and Calculation of Indicators

In this study, digitalization is operationalized through four technological pillars: (i) connectivity, (ii) precision agriculture, (iii) robotics, and (iv) farm management information systems (FMIS). The technology adoption rate was calculated exclusively for commercial farms (Standard Output > €100,000), using the following Equation (1):

$$Rtech, i = \frac{Nadopt,\ i}{Ntotal, i} \times 100 \tag{1}$$

R*tech,i* represents the adoption rate of the technology under analysis in Member State$_i$;

N*adopt,i* represents the number of commercial farms (and their corresponding area) in Member State *i* that use the technology under analysis;

N*total,i* represents the total number of commercial farms (and their corresponding total agricultural area) in Member State *i* (SO > €100,000).

This methodological formulation ensures that the digitalization indicator exclusively reflects the active economic segment of agriculture, reducing statistical distortions generated by the inclusion of non-commercial or subsistence farms. The percentage rates obtained for each pillar were directly incorporated into the construction of the DFI composite index, as all four dimensions are expressed on the same percentage scale (0–100%). Therefore, no additional normalization procedure was necessary, as the indicators were already comparable across the four dimensions analyzed [43,44].

2.3. Aggregation of the Pillars and Calculation of the DFI Index

The Digital Farm Index (DFI) was constructed by aggregating the four analyzed technological pillars. In accordance with methodological recommendations for constructing composite indicators, an asymmetric weighting scheme was utilized. The allocation of these weights was not arbitrary but was rigorously grounded in agricultural economics literature, reflecting cost barriers (CAPEX vs. OPEX), agronomic utility, and adoption rates. An equal-weight approach would have distorted the economic reality of the market, erroneously equating the massive investment effort of a heavy robotic system with that of a software license.

Thus, Precision Agriculture (35%) received the maximum weight as literature identifies it as the 'operational core' of any smart farm. This technology generates immediate field results (input optimization, yield increases) and represents the investment with the fastest and most secure return on capital (ROI) for European farmers [31,45,46]. Robotics (25%) received the second-largest weight, representing the technological frontier. Although it addresses labor shortages, acquiring autonomous systems involves an extremely high financial risk (CAPEX), with adoption severely constrained by farm size and budget [47,48].

In contrast, Connectivity (20%) and Farm Management Information Systems (FMIS–20%) received lower weights, acting as support infrastructures [10,36,49]. Economically, implementing a network or purchasing a software subscription (SaaS) generates significantly lower initial barriers, transforming the investment into a current operating expense (OPEX) [8]. Furthermore, the practical utility of an FMIS program is completely dependent on physical field equipment, being unable to produce agronomic results on its own [50].

The final index score was calculated by applying these asymmetric weights to the adoption rates of the four pillars, according to Equation (2):

$$DFIi = (Pconn, i\ \times\ 0.20) + (Pprec, i\ \times\ 0.35) + (Prob, i\ \times\ 0.25) + (Pfmis, i\ \times\ 0.20) \tag{2}$$

where

P*conn,i* represents the percentage adoption rate of connectivity;

P*prec,i* represents the percentage adoption rate of precision agriculture;

P*rob,i* represents the percentage adoption rate of robotics;

P*fmis,i* represents the percentage adoption rate of farm management information systems (FMIS).

This methodological procedure was applied separately to the two analytical dimensions of the study: DFI-Farms (based on the number of farms) and DFI-Hectares (based on agricultural area). The final score, expressed as a percentage, reflects the aggregate level of digital maturity for each Member State analyzed.

To ensure the transparency of the financial modeling, the CAPEX thresholds calculated in this study are based on three fundamental economic premises: (1) Standardized assessment: Equipment prices are standardized across the analyzed Member States and indexed to 2026 EUR values, mitigating short-term market volatility; (2) Cost isolation: The mathematical equations reflect pure capital expenditures (CAPEX) as an initial entry barrier, intentionally keeping dynamic operational expenditures (OPEX, e.g., routine maintenance, software subscriptions) outside the scope of the model; and (3) Amortization horizon: The investment burden is modeled under the premise of a standard five-year linear depreciation cycle, reflecting the typical physical and technological obsolescence rate of digital agricultural technologies.

2.4. Modeling Investment Costs and Defining Technology Scenarios

The financial estimate was calculated using CAPEX modeling for three investment scenarios, based on actual market prices and indexed to 2026:

Economic Scenario—minimal configuration focused on technological compliance: (€46,893).

Efficiency Scenario—configuration optimized to maximize the cost–benefit ratio: (€85,274).

Performance Scenario—advanced configuration focused on enhancing production performance: (€134,835).

For each investment scenario and for each Member State, the Cost of Digitalization per Hectare ($C_{ha,i}$) was estimated. Given the predominantly fixed nature of a significant portion of digital investments (CAPEX), the calculation was performed by dividing the total cost of the technology package by the average utilized agricultural area ($S_{avg,i}$) of commercial farms, in order to isolate the effect of economies of scale [29]. The formula used is presented in Equation (3):

$$Cha,i = \frac{Kconn + Kprec + Krob + Kfmis}{Savg,i} \tag{3}$$

K represents the average acquisition cost (CAPEX) for each technological pillar,

S_{avg} represents the average agricultural area of commercial farms in Member State *i*.

The resulting indicator, $C_{ha,i}$[€/ha], expresses the investment threshold per unit of area and was used to test hypothesis H2 regarding economies of scale.

2.5. Statistical and Multivariate Analysis

Data processing involved the use of the R programming environment (the bibliometrix package, Biblioshiny interface) for scientific literature mapping [51] and JASP software (version 0.95.4.0) for inferential analysis [52]. The log-linear regression analysis used to test for economies of scale (H2) was performed in Microsoft Excel, based on logarithmically transformed variables, to ensure transparency in the relationship between average farm size and investment cost per hectare. The normality of the distributions was verified using the Shapiro–Wilk test, and the threshold for statistical significance was set at $p < 0.05$ for the inferential analyses.

To assess regional disparities (hypothesis H1), Member States were grouped into two geographic categories: West (Austria, Belgium, Finland, France, Germany, Ireland, Portugal, Sweden, the Netherlands) and East (Czechia, Cyprus, Croatia, Estonia, Greece, Latvia, Romania, Slovakia, Hungary). Differences between these two groups regarding DFI-Farms and DFI-Hectares values were analyzed using the Independent Samples *t*-test, and the effect size was assessed using Cohen's d. Homogeneity of variances was tested using the Brown–Forsythe test, and distributions were graphically represented using Raincloud Plots.

To test for economies of scale (H2), the relationship between the average size of commercial farms and capital expenditure (CAPEX) per hectare was analyzed using simple linear regression in a log-log specification. Thus, the transformed variables $\ln(S_{avg})$, representing the natural logarithm of the average farm size, and $\ln(C_{ha})$, representing the natural logarithm of the investment cost per hectare, were used. Model performance was evaluated using the coefficient of determination R^2, the statistical significance level of the coefficients, and visualization of the relationship via log-log scatterplots with fitted regression lines.

To identify the structural profiles of the member states, hierarchical clustering was used, based on the variables DFI-Farms, DFI-Hectares, S_{avg} (average area), and C_{ha}, econ (investment cost per hectare corresponding to the economic scenario). The analysis was performed on standardized variables, using Euclidean distance and the Ward.D aggregation method. The final solution was extracted in the form of three clusters. The interpretation of the profiles was supported by the analysis of the clusters' standardized means and by their visual representation using Cluster Mean Plots.

To isolate the effect of economies of scale from the influence of the regional ecosystem, predictive modeling using multiple linear regression (MLR) and Pearson's correlation analysis was employed. Two regression models were specified, with the two dimensions of digital maturity (DFI-Hectares and DFI-Farms) as dependent variables. The predictors included simultaneously in both models were the natural logarithm of the average farm area ($\ln S_{avg}$) and geographic location (introduced as a dummy variable: West = 1, East = 0). The models were evaluated based on the adjusted coefficient of determination (adjusted R^2) and Fisher's F-test. To ensure transparency regarding distributional disparities and visual validation of the models, advanced Raincloud Plots were generated using JASP software (version 0.95.4).

2.6. Methodological Limitations

Although the methodological framework is robust, the study has certain inherent limitations. First, the cross-sectional design of the Eurostat datasets provides a static snapshot of the situation as of the reference year; indexing capital expenditures (CAPEX) to the year 2026 enhances economic realism but cannot substitute for a comprehensive longitudinal analysis of adoption dynamics. Second, the use of nationally aggregated data may obscure intra-regional heterogeneity (e.g., disparities among NUTS-2 development regions). Third, restricting the research universe exclusively to commercial farms (Standard Output > €100,000) limits the extrapolation of results to the subsistence and semi-subsistence farming sector. However, this selection is methodologically justified to neutralize structural distortions and to allow for the analytical isolation of agricultural segments with a real capacity for capitalization and technology adoption.

Fourth, the current analysis covers 18 Member States (out of a total of 27), because the Eurostat datasets used—particularly those relating to digitalization indicators by technological pillars—do not provide complete and comparable information for the reference year regarding the commercial holdings segment with a Standard Output > €100,000. This limitation stems strictly from data availability constraints and not from an arbitrary sample selection. However, since major agricultural actors (such as Spain, Italy, and Poland) or highly digitalized countries (such as Denmark) are missing, this omission introduces a potential selection bias. Although this limits the absolute generalization of the aggregated

European averages to the entire EU-27, the fundamental structural mechanisms identified in this study—namely, technological indivisibility, economies of scale, and CAPEX entry barriers—remain theoretically robust for different agricultural typologies.

3. Results

3.1. Bibliometric Analysis of the Literature on the Digitalization of Agriculture

The bibliometric analysis highlights the rapid consolidation of research on the digitalization of agriculture as a distinct interdisciplinary field. The analyzed corpus covers the period 2000–2025 and includes 3500 documents published in 313 scientific sources, authored by 15,995 authors. The average annual growth rate of publications is 12.96%, confirming the accelerated expansion of academic interest in Agriculture 4.0. Furthermore, the average of 5.62 co-authors per document and the 28.46% share of international co-authorship indicate a high level of scientific collaboration and the global nature of this research field. At the same time, the average of 22.75 citations per document and the average age of publications of 4.37 years suggest both the high scientific visibility of the corpus and the relatively recent and dynamic nature of the analyzed bibliographic database.

The thematic structure of the literature confirms the existence of well-defined conceptual clusters. The thematic map highlights two driving themes, characterized by high levels of centrality and development: the yield–remote sensing–model cluster and the agriculture–management–productivity cluster. The first reflects the literature's intense focus on crop monitoring and yield modeling, while the second captures the managerial and economic dimensions of digitalization. At the same time, the machine learning–deep learning–classification group is positioned among emerging themes, suggesting that methods based on artificial intelligence are becoming increasingly influential, though they are still undergoing conceptual consolidation in agricultural applications. The precision agriculture–quality–variability theme is identified more as a basic theme, indicating that, although precision agriculture remains the terminological core and foundation of the field, the current dynamics of research are being driven by more specialized and technologically advanced subthemes.

The co-occurrence network of keywords confirms the central role of the concept of precision agriculture, which serves as the primary link between the agronomic and computational dimensions of the field. Three major thematic clusters emerge around this concept. The first is associated with machine learning, classification, deep learning, computer vision, and artificial intelligence, reflecting the accelerated integration of algorithmic methods into agricultural data analysis. The second cluster is built around the terms yield, remote sensing, crop, irrigation, water, and productivity, highlighting the continuity of the applied tradition focused on crop performance and input optimization. The third cluster, dominated by terms such as management, technology, IoT, systems, adoption, and sustainability, suggests that the literature is moving beyond a strictly technological approach and evolving toward a systemic perspective, in which data integration and decision support become essential elements.

Consequently, the bibliometric analysis goes beyond a merely descriptive role, functioning as an explicit theoretical foundation for the creation of the Digital Farm Index (DFI). The architecture of the index and the selection of its four constituent pillars (Connectivity, Precision Agriculture, Robotics, and FMIS) do not represent an arbitrary methodological choice; rather, they empirically translate the major thematic clusters identified in the co-occurrence network of the global scientific literature (Figure 1c). Through this architecture, the DFI extracts theoretical concepts validated by the dynamics of international research and transforms them into measurable economic indicators. This alignment ensures a profound structural integration between the bibliometric analysis of the literature and the empirical assessment of digital maturity at the European farm level.

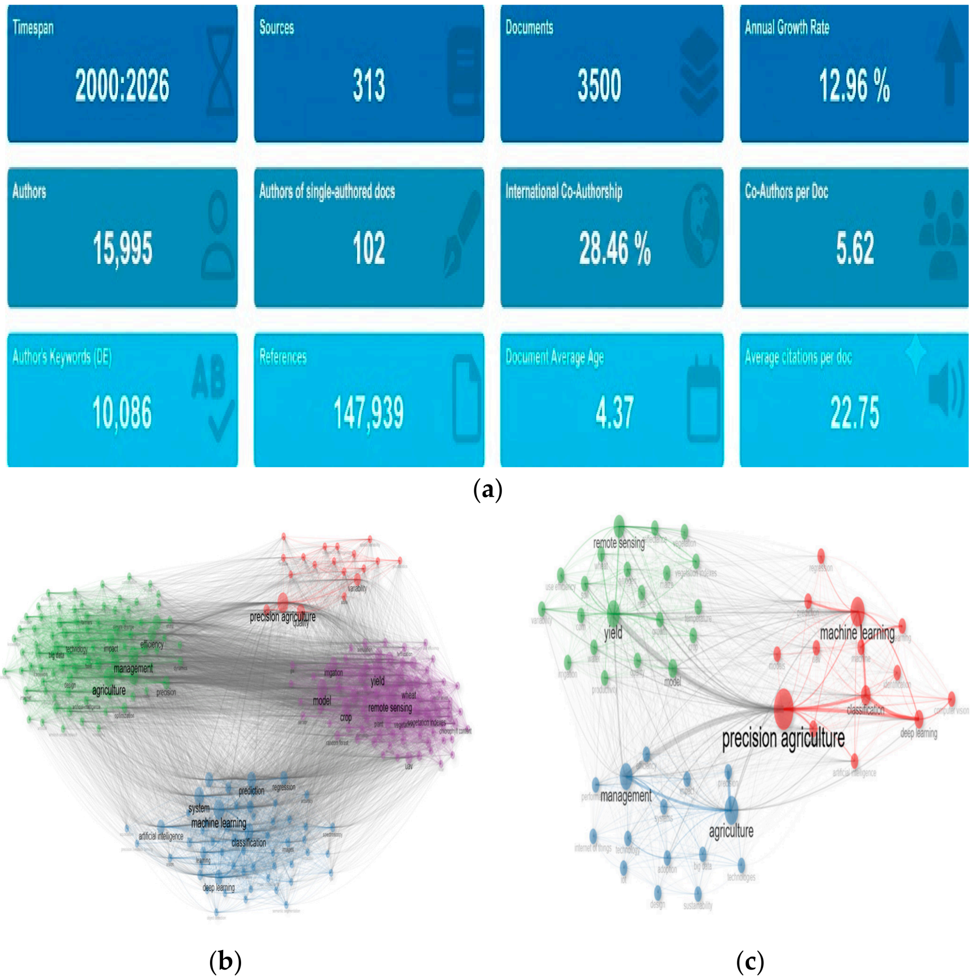

Figure 1. Bibliometric profile of the research field on agricultural digitalization: (**a**) annual scientific production; (**b**) thematic map; (**c**) keywords co-occurrence network.

3.2. Gross Adoption Rates of Digital Technologies Among Commercial Farms

An analysis of gross adoption rates reveals a clear hierarchy of digitalization dimensions among commercial farms in the Member States analyzed. Connectivity is the pillar with the highest level of coverage; in several countries, internet access is approaching universal coverage across many agricultural systems. The highest adoption rates are recorded in Czechia, Germany, Ireland, Latvia, and Slovakia, while Cyprus, Greece, and Portugal consistently rank at the lower end of the distribution. This result indicates that primary digital infrastructure is already widespread in certain agricultural systems in northern and central Europe, but remains underdeveloped in some Mediterranean countries.

Unlike the connectivity pillar, precision agriculture and robotics show much greater variation across countries, marking the transition from infrastructural digitalization to operational and investment-driven digitalization. Estonia, Finland, and Ireland stand out for their high levels of precision agriculture adoption, while Cyprus, Romania, and Slovakia record values significantly below the sample average. In the case of robotics, the distribution of data is even more polarized: Czechia represents a positive outlier, with a very high adoption rate, in stark contrast to Cyprus, Greece, and Portugal, which remain at minimal levels. This profile suggests that capital-intensive technologies are associated with a more polarized distribution of adoption among member states.

The adoption of Farm Management Information Systems (FMIS) exhibits a specific adoption pattern that differs from that observed for tangible technologies (precision farming and robotics). Finland, France, Ireland, and the Netherlands have the highest levels of FMIS adoption, indicating the existence of mature digital ecosystems where data flows are systematically integrated into operational management. In contrast, Belgium, Cyprus, Greece, and Romania occupy the lower positions in the ranking, suggesting limited adoption of digital management tools. This gap reflects not only a technological barrier but also a lack of managerial expertise, resulting in a reduced ability to convert raw data into informed economic decisions. This disparity between investment in hardware and the use of decision-support software points to a functional disconnect in certain Member States.

A cross-sectional analysis of adoption rates confirms the existence of a phased hierarchy of digital maturity: connectivity serves as the basic infrastructure, precision agriculture marks the transition toward the digitalization of operational workflows, and robotics reflects the degree of technological and capital (CAPEX) intensification, while FMIS solutions capture the managerial and decision-making dimension of the transformation. Countries such as Estonia, Finland, France, and Ireland exhibit balanced and advanced digital profiles across all analyzed dimensions. In contrast, Cyprus, Greece, Portugal, and Romania exhibit converging structural vulnerabilities, indicating fragmented digitalization dependent on entry barriers. These results justify the use of a composite index (DFI), capable of capturing not only individual levels but also the complementarity between the tangible and intangible dimensions of European agricultural digitalization.

3.3. Assessing Digital Maturity Using the DFI Index at the Commercial Farm Level

Aggregating the four pillars of digitalization at the commercial farm level, using the established weighted formula—connectivity 20%, precision agriculture 35%, robotics 25%, and FMIS 20%—highlights significant differences among the Member States analyzed. The asymmetric weighting scheme was designed to reflect the operational complexity and varying investment intensity of the four pillars. Thus, the index more clearly highlights the countries where digitalization remains concentrated in basic infrastructure and distinguishes them from those that have advanced toward more complex operational and managerial technologies. DFI-Farms values range from low levels in Cyprus (6.66) and Greece (11.04) to the maximum value recorded in Finland (77.31), confirming the existence of significant gaps in digital maturity among European agricultural systems. Across the entire sample analyzed, comprising 461,280 commercial farms, the weighted average of the index is 58.61%.

At the top of the distribution, a group of countries with high levels of digital maturity stands out: Finland (77.31), Ireland (71.39), Estonia (69.18), France (68.64), and Sweden (62.37). These countries combine high levels of connectivity with substantial adoption rates of operational and managerial technologies. Precision agriculture, a pillar accounting for 35% of the DFI, plays a significant role in these countries' rankings, particularly in the case of Ireland, where the adoption rate of these solutions reaches 86.09% among commercial farms. France is also a relevant case, as, although it accounts for a very high proportion of the total commercial farms analyzed, it maintains a high DFI score, suggesting relatively widespread technological diffusion across the national agricultural system.

In the upper-middle segment are Germany (61.88), Czechia (58.14), Latvia (57.01), and Belgium (52.62). In these cases, the aggregate score reflects distinct technological configurations. For example, Czechia's position is supported by a very high rate of robotics adoption (98.86%), which compensates for the lower level of precision agriculture. Germany presents a more balanced profile across operational technologies, combining precision agriculture (68.76%) with robotics (42.06%). A median subgroup consists of the Netherlands

(48.32), Croatia (46.93), Hungary (45.59), and Austria (42.73), where digitalization is present but does not simultaneously reach high levels across all capital-intensive pillars.

At the lower end of the distribution are Slovakia (31.03), Portugal (23.77), and Romania (20.88), followed by Greece (11.04) and Cyprus (6.66). Applying the asymmetric weighting scheme highlights more clearly the vulnerabilities of these agricultural systems, particularly when digitalization remains limited to connectivity and is not supported by the adoption of operational technologies or managerial tools. The case of Romania illustrates this imbalance: although internet access is available on 50.84% of commercial farms, adoption rates for FMIS (5.58%) and precision agriculture (15.13%) remain among the lowest in the sample.

Consequently, the distribution of the DFI-Farms index shows that the digital maturity of commercial farms in the European Union depends not only on the existence of digital infrastructure, but also on the ability to integrate more complex operational and managerial technologies. Connectivity is a necessary but not sufficient condition for substantial digital transformation, and the absence of technological and managerial pillars keeps some agricultural systems in an early stage of digital maturity.

3.4. Gross Technology Adoption Rates at the Level of Agricultural Land

An analysis of gross adoption rates relative to utilized agricultural area indicates a higher concentration of digitalization among large-scale farms compared to the distribution observed across the total number of farms. This difference suggests that the digital transformation process is primarily driven by commercial actors with extensive agricultural land, who are better able to recoup technological investments. The connectivity pillar shows the highest coverage rates by area, exceeding 97% in countries such as Czechia, Estonia, Finland, Germany, Ireland, Latvia, Slovakia, and Sweden. This result shows that, in these agricultural systems, basic digital infrastructure is present across a very high proportion of the cultivated area, providing a necessary foundation for the expansion of precision agriculture technologies. In contrast, Greece (15.99%), Cyprus (19.78%), and Portugal (21.76%) have the lowest coverage levels, indicating the persistence of significant limitations in access to agricultural digital infrastructure.

The adoption of precision agriculture shows a distribution that is relatively similar to that of connectivity, but with a more pronounced polarization among countries. The highest levels of territorial coverage of precision technologies are recorded in Ireland (87.89%), Estonia (87.82%), Finland (86.01%), Germany (82.11%), and France (78.12%). In contrast, Cyprus (1.02%), Slovakia (17.27%), Greece (19.08%), and Romania (23.85%) occupy the lower end of the distribution. These results suggest that the adoption of precision agriculture is more advanced in agricultural systems characterized by established commercial farms and a greater capacity for the operational integration of digital technologies.

In the case of robotics, the distribution of data indicates an even more pronounced polarization, reflecting the capital-intensive nature of these technologies. Finland (63.01%), Latvia (56.90%), Sweden (56.90%), the Netherlands (56.60%), and France (53.89%) have the highest shares of area covered by automated solutions. At the opposite end of the spectrum, Greece (5.58%), Cyprus (6.50%), and Portugal (6.53%) remain at very low adoption levels. This pattern suggests that the integration of robotics into agricultural processes is associated with the existence of farms capable of sustaining high fixed investments and spreading costs over larger areas.

The adoption of farm management information systems (FMIS) also reveals significant differences among the countries analyzed. Czechia has the highest rate, with 99.37% of commercial agricultural land covered by FMIS solutions, followed by France (87.50%), Finland (84.84%), the Netherlands (83.46%), and Estonia (76.95%). At the opposite end of the spectrum, Greece (2.68%), Cyprus (8.24%), and Romania (9.58%) have the lowest

https://doi.org/10.3390/agriculture16141565

figures, indicating limited use of digital management tools. This result suggests that the managerial dimension of digitalization, associated with data integration and the monitoring of operational flows, is better developed in established agricultural systems. The low figures observed in some countries indicate difficulties in transitioning from data collection to its use in planning, economic monitoring, and decision-making processes.

Thus, the distribution of gross adoption rates across agricultural land indicates a higher concentration of digitalization in large commercial farms. Countries such as Estonia, Finland, France, Ireland, and Sweden exhibit relatively balanced and advanced digital profiles, while Cyprus, Greece, Portugal, and Romania show low values across multiple pillars, suggesting fragmented digitalization. This finding supports the idea that the adoption of Agriculture 4.0 technologies is not evenly distributed but follows a selective pattern, associated with a greater capacity for capitalization and investment absorption.

Based on these gross adoption rates at the level of agricultural land, the next step is to aggregate the four dimensions into a composite index capable of capturing the overall level of digital maturity of the land farmed by commercial farms.

3.5. Assessing Digital Maturity Using DFI at the Level of Agricultural Land

The weighted aggregation of the four pillars of digitalization at the level of utilized agricultural area, as measured by the DFI-Hectares indicator, reveals a higher level of digital maturity than that observed at the level of the total number of farms. The average value of DFI-Hectares is 64.06%, compared to 58.61% for DFI-Farms, suggesting a greater concentration of Agriculture 4.0 technology adoption on larger farms. This difference is consistent with the hypothesis of economies of scale, as farms with larger areas have a greater capacity to amortize the fixed costs associated with precision technologies, robotics, and management information systems. DFI-Hectares index values vary substantially across Member States, ranging from 7.59 in Cyprus to 82.33 in Finland, indicating significant differences in the degree of digital integration of commercial agricultural land. These results suggest that digitalization at the territorial level is influenced by both farm size and the capacity of agricultural systems to support complex technological investments.

The highest DFI-Hectares index values are recorded in Finland (82.33), France (76.73), Estonia (76.23), Ireland (74.04), and Sweden (70.48). These countries combine high levels of connectivity with widespread adoption of precision agriculture, robotics, and FMIS technologies. France is a notable case, as it accounts for 35.03% of the total area of the analyzed sample—exceeding 21 million hectares—while also maintaining a high DFI-Hectares score. This result is supported by high levels of precision agriculture adoption (78.12%) and the widespread integration of FMIS solutions (87.50%). Overall, these figures suggest the existence of agricultural systems where critical mass in production is associated with relatively advanced technology diffusion across commercial farmland.

A second group of countries, with upper-middle values on the DFI-Hectares index, includes Latvia (69.29), Germany (69.26), Czechia (60.44), the Netherlands (57.84), Hungary (57.66), Belgium (55.05), and Croatia (53.57). In these agricultural systems, the aggregate scores reflect different technological configurations. Germany stands out for its high level of precision agriculture adoption (82.11%), associated with the use of GNSS-assisted guidance technologies and crop mapping tools. Czechia presents a distinct profile, characterized by very high adoption of FMIS solutions across commercial farmland (99.37%), while the share of robotics remains more moderate (24.90%). These patterns suggest that Member States can achieve similar levels of digital maturity through different combinations of technological pillars, depending on the specific characteristics of their agricultural systems and their orientation toward data-driven management.

At the lower end of the distribution are Austria (46.11), Slovakia (38.40), Portugal (29.43), and Romania (25.83), while Greece (11.81) and Cyprus (7.59) have the lowest DFI-Hectares index values. The case of Romania is relevant for interpreting the difference between available agricultural land and the actual level of digitalization. Although Romania accounts for nearly 9% of the total area of the analyzed sample, adoption levels of operational and managerial technologies remain low. Precision agriculture covers 23.85% of commercial agricultural land, and FMIS solutions 9.58%, suggesting limited integration of advanced digital tools. This configuration indicates the existence of an implementation gap, in which territorial size does not automatically translate into a high level of digital maturity.

A direct comparison of the DFI-Hectares and DFI-Farms results highlights a significant asymmetry in the digital transformation process. The fact that the level of digitization relative to land area consistently exceeds the level calculated based on the number of farms suggests that Agriculture 4.0 technologies are concentrated primarily on large-scale farms. This difference is consistent with the logic of technological indivisibility, as complex assets, such as specialized agricultural drones or advanced remote sensing systems, entail high initial costs (CAPEX), whose economic justification depends on the possibility of amortization over large areas. Thus, a comparative analysis of the two variants of the DFI index indicates that European digital divides are driven not only by the pace of technology adoption but also by the farm-size structure of agricultural systems. This configuration favors farms capable of generating economies of scale and may limit small farms' access to advanced digital technologies.

Following a comparative assessment of digital maturity at the level of commercial farms and agricultural land, the analysis is expanded to include statistical testing of regional disparities and an examination of the relationship between digitalization, farm structure, and implementation costs per hectare.

Therefore, a higher DFI-Hectares score should not be misinterpreted as a sign of widespread digital maturity across the entire agricultural sector; rather, it reflects a massive concentration of technological adoption among a limited number of large-scale farms that dominate the agricultural landscape.

3.6. Regional Disparities, Economies of Scale, and Structural Mechanisms of Digitalization

3.6.1. Regional Differences Between Western and Eastern Countries

To assess the existence of regional disparities in digital maturity, DFI index values were analyzed comparatively between the group of Western countries (n = 9) and the group of Eastern countries (n = 9). Testing the statistical assumptions indicated that the distributions did not deviate significantly from normality, and the Brown–Forsythe test did not reveal significant differences in variances between the two groups. Therefore, the comparison was performed using the *t*-test for independent samples.

In the case of DFI-Farms, Eastern states recorded a mean of 38.50, compared to 56.56 in the group of Western states. The difference is descriptively consistent but does not reach the conventional threshold for statistical significance ($t = -1.836$; $p = 0.085$). However, the effect size is large (Cohen's $d = -0.866$), suggesting a substantial separation between the two groups from a practical standpoint. This result indicates a lower level of digital maturity among agricultural enterprises in Eastern European countries and suggests that access to basic digital infrastructure is insufficient in the absence of more consistent adoption of operational and managerial technologies.

With regard to DFI-Hectares, the Eastern countries recorded an average of 44.53, while the Western group reached 62.36. In this case as well, the difference is not statistically significant at the 5% threshold ($t = -1.643$; $p = 0.120$), but the effect size remains moderate-to-high (Cohen's $d = -0.774$). The persistence of this gap in terms of cultivated area indicates that regional differences are not limited to the number of digitalized farms, but also extend to the intensity of digital technology integration across the agricultural area in use.

The results show that Western Member States exhibit higher average values of digital maturity, both at the farm level and at the level of agricultural land. However, the absence of statistical significance at the 5% threshold indicates that H1 is only partially supported. The direction of the differences is consistent with the expected West–East digital divide, and the medium-to-large effect sizes suggest relevant practical differences between the two groups. Nevertheless, the statistical evidence is not strong enough to confirm H1 under the conventional $p < 0.05$ criterion. Therefore, the West–East contrast should be interpreted with caution and supplemented by an analysis of other structural mechanisms. Although Eastern Member States have, on average, larger commercial farms, this structural advantage does not automatically translate into a comparable level of digital maturity. The difference of approximately 18 points between the averages of the two groups suggests that farm size is a favorable but not sufficient condition for accelerating digitalization. In the absence of an adequate support ecosystem, sufficient investment capacity, and a favorable institutional infrastructure, the structural advantages associated with larger farm sizes remain partially untapped.

3.6.2. Economies of Scale and Modeling Investment Barriers Using Multiple Scenarios

The relationship between the average size of commercial farms and the cost of digitalization per hectare highlights a fundamental scale effect, driven by the predominantly fixed nature of investments in Agriculture 4.0 technologies. Because the unit cost (Cha) is calculated by dividing a fixed capital expenditure (CAPEX) by the average farm size (Savg), the relationship between these two variables is mathematically predetermined to be inversely proportional. Therefore, the log-linear representation in Figure 2 does not constitute an independent empirical finding based on an econometric regression with statistical error. Instead, it serves as a deterministic simulation of capital amortization thresholds.

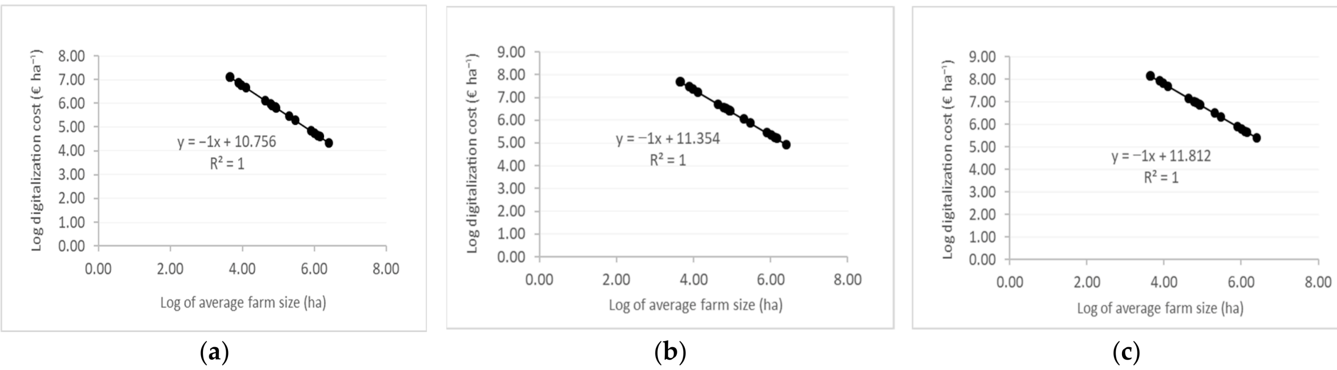

Figure 2. Log-linear relationship between average farm size and digitalization cost per hectare under three investment scenarios: (**a**) economic scenario; (**b**) efficiency scenario; and (**c**) performance scenario. In all three cases, the fitted regression line illustrates the inverse association between farm size and unitary investment burden.

By converting the cost function into a logarithmic form, the model follows Equation (4) with perfect unitary elasticity:

$$\ln(Cha) = \ln(CAPEX) - 1.000\ ln\ (Savg) \tag{4}$$

The coefficient associated with the natural logarithm of the area, mechanistically equal to -1.000, demonstrates that an increase in farm size reduces the unit investment burden in direct proportion. The fact that the model fully explains the data variation ($R^2 = 1.000$)

confirms the purely deterministic nature of this cost curve. The vertical shifts in the curves, visible in Figure 2, are driven by the variation in the intercept (ln(CAPEX)), which reflects the specific entry thresholds for each investment configuration.

In the Economic scenario, the minimum entry barrier is defined by digitalization costs per hectare ranging from €77/ha in Slovakia to €1221/ha in Greece. In the Efficiency scenario, the same relational structure is maintained, but the entire cost curve is shifted upward, with the range of values extending from €140/ha to €2221/ha. In the Performance scenario, investment pressure becomes even higher, with unit costs exceeding €3500/ha for small-scale commercial farms.

Consequently, although the relationship is mathematically determined, the simulation demonstrates a profoundly asymmetric economic reality: the national farm-size structure acts as a relentless selection filter. Digitalization mechanistically favors agricultural systems capable of generating economies of scale, transforming capital barriers (CAPEX) into a mechanism that reproduces digital development gaps at the European level.

3.6.3. The Gap Between Technology Adoption and Digital Management Maturity

A comparative analysis of the pillars of digitalization highlights the existence of asymmetries between the operational dimension of digital transformation and the managerial integration of data. As shown by the gross adoption rates presented in Tables 1 and 2, connectivity and, in many cases, precision agriculture or robotics achieve higher penetration levels than farm management information systems (FMIS), particularly in countries characterized by intermediate digital profiles. This distribution suggests that digital investments are primarily directed toward physical infrastructure and operational farm technologies, while the managerial component of digitalization is being adopted more slowly and unevenly.

Table 1. Raw adoption rates of digital technologies at the farm level in the selected EU Member States.

Country	Internet Access (%)	Precision Agriculture (%)	Robotics (%)	FMIS (%)
Austria	97.74	33.71	13.85	39.58
Belgium	84.23	61.01	32.86	31.05
Croatia	90.91	54.55	16.56	27.60
Cyprus	17.65	1.47	5.15	6.62
Czechia	98.86	20.45	98.86	32.47
Estonia	96.23	79.87	34.59	66.67
France	89.58	70.26	39.31	81.53
Finland	97.14	79.88	55.12	80.71
Germany	98.53	68.76	42.06	37.95
Greece	15.37	16.01	7.47	2.45
Ireland	99.01	86.09	30.45	69.24
Hungary	94.70	39.64	14.98	45.16
Latvia	100.00	55.78	40.82	36.39
Netherlands	73.00	19.93	48.33	73.30
Portugal	20.06	44.68	4.27	15.28
Romania	50.84	15.13	17.22	5.58
Slovakia	99.61	8.59	7.42	31.25
Sweden	96.95	54.38	47.78	60.00

Table 2. Raw adoption rates of digital technologies at the hectare level in the selected EU Member States.

Country	Internet Access (%)	Precision Agriculture (%)	Robotics (%)	FMIS (%)
Austria	97.86	39.66	14.69	44.92
Belgium	84.53	65.74	32.14	35.49
Croatia	93.44	63.89	18.10	39.96
Cyprus	19.78	1.02	6.50	8.24
Czechia	99.37	41.33	24.90	99.37
Estonia	97.22	87.82	42.62	76.95
France	92.07	78.12	53.89	87.50
Finland	97.51	86.01	63.01	84.84
Germany	99.19	82.11	39.93	53.52
Greece	15.99	19.08	5.58	2.68
Ireland	100	87.89	36.51	70.77
Hungary	94.98	55.54	23.91	66.42
Latvia	100	72.76	56.90	48.00
Netherlands	83.27	29.55	56.60	83.46
Portugal	21.76	55.92	6.53	19.36
Romania	58.07	23.85	15.80	9.58
Slovakia	99.75	17.27	13.28	45.41
Sweden	97.01	65.85	56.90	69.01

This trend is also indirectly supported by the distribution of the aggregate DFI-Farms and DFI-Hectares scores, presented in Tables 3 and 4, which show that high-performing countries tend to combine the technological and managerial dimensions of digitalization more coherently, while countries with low scores remain characterized by partial and unbalanced adoptions. The result indicates that technological modernization does not automatically imply the development of an equivalent capacity to integrate and use data in the decision-making process. Thus, farms may adopt equipment, sensors, guidance systems, or automated technologies without the information they generate being systematically used in planning, economic monitoring, and managerial control.

Table 3. Digital Farm Index (DFI-Farms) scores and ranking across the selected EU Member States.

Country	DFI-Farms
Finland	77.31
Ireland	71.39
Estonia	69.18
France	68.64
Sweden	62.37
Germany	61.88
Czechia	58.14
Latvia	57.01
Belgium	52.62
Netherlands	48.32
Croatia	46.93
Hungary	45.59
Austria	42.73
Slovakia	31.03
Portugal	23.77
Romania	20.88
Greece	11.04
Cyprus	6.66

Table 4. Digital Farm Index (DFI-Hectares) scores and ranking across the selected EU Member States.

Country	DFI-Hectares
Finland	82.33
France	76.73
Estonia	76.23
Ireland	74.04
Sweden	70.48
Latvia	69.29
Germany	69.26
Czechia	60.44
Netherlands	57.84
Hungary	57.66
Belgium	55.05
Croatia	53.57
Austria	46.11
Slovakia	38.40
Portugal	29.43
Romania	25.83
Greece	11.81
Cyprus	7.59

From a structural perspective, this model is consistent with the literature on the hardware-software paradox, according to which the digitalization of agriculture often progresses more rapidly through the acquisition of tangible technologies than through the software and managerial integration of data flows. Consequently, the results suggest that the digital maturity of a farm should be assessed not only in terms of the presence of technology, but also in terms of the level of functional integration between digital infrastructure, operational use, and the managerial capacity to transform data into economic decisions.

Consequently, the gap between technological adoption and managerial maturity suggests that a farm's digital transformation cannot be assessed solely on the basis of technical equipment but also on the ability to functionally integrate data into economic decision-making.

3.6.4. Structural Profiles of Member States

Hierarchical cluster analysis identified three distinct structural profiles of Member States, integrating the level of digital maturity (DFI-Farms and DFI-Hectares), the average size of commercial farms, and the cost of digitalization per hectare. The extracted three-cluster solution explains 63.2% of the total data variation (R^2 = 0.632), indicating a consistent ability to differentiate between groups. The Silhouette score (0.390) supports the interpretability of the clustering, suggesting the existence of structurally distinct profiles (Figure 3).

Cluster 1: Structurally Vulnerable Systems Facing High Barriers to Entry (5 countries)

This group includes Austria, Belgium, Cyprus, Greece, and the Netherlands. The profile is defined by the smallest average size of commercial farms in the sample, approximately 48 ha, a fact that is automatically associated with the highest burden of digitalization costs per hectare (an average of €1008.70/ha in the economic scenario). Due to these high fixed barriers, the average level of digitalization is low (DFI-Farms: 32.27%; DFI-Hectares: 35.68%). The inclusion of some Western countries in this group alongside Cyprus and Greece demonstrates that land fragmentation acts as a universal barrier to entry: even in developed agricultural systems, smaller farms face difficulties in amortizing precision equipment and robotics, limiting the country's aggregate digital maturity.

Cluster 2: Countries with advanced digitalization and a structure conducive to adoption (10 countries)

This cluster includes Croatia, Czechia, Estonia, France, Finland, Germany, Ireland, Hungary, Latvia, and Sweden. The group comprises countries characterized by high levels of digital maturity and a structure relatively conducive to adoption. The average farm size, approximately 239 ha, allows for a more efficient distribution of fixed costs, with the average cost of digitalization being €265.31/ha in the economic scenario. This configuration is associated with the highest average levels of digital maturity in the sample: 61.84% at the farm level and 69.00% at the area level. The result suggests that a high level of DFI is associated with the interaction between capitalization capacity, farm size, and the relatively consistent adoption of tangible and intangible solutions.

Cluster 3: Systems with economies of scale but low digital maturity (3 countries)

This small group, consisting of Portugal, Romania, and Slovakia, exhibits a unique combination of economies of scale and low levels of digital maturity. The countries in this cluster have the largest average size of commercial farms in the sample, approximately 372 ha, and, consequently, the lowest digitalization investment costs per hectare, averaging €179.14/ha in the economic scenario. However, average levels of digital maturity are the lowest (DFI-Farms: 25.23%; DFI-Hectares: 31.22%). This result shows that economies of scale are a favorable but not sufficient condition for digitalization. In these countries, barriers appear to be associated not only with the area capable of amortizing CAPEX, but also with the availability of investment capital, the level of digital skills, the quality of connectivity infrastructure, and institutional support policies.

The clustering results show that European digital divides are not limited to a simple West–East geographic polarization, but reflect a more complex structural stratification. The economic feasibility of digitalization differentiates countries based on their vulnerability to fixed costs, their capacity to scale investments, and their ability to transform the advantage of size into effective digital maturity.

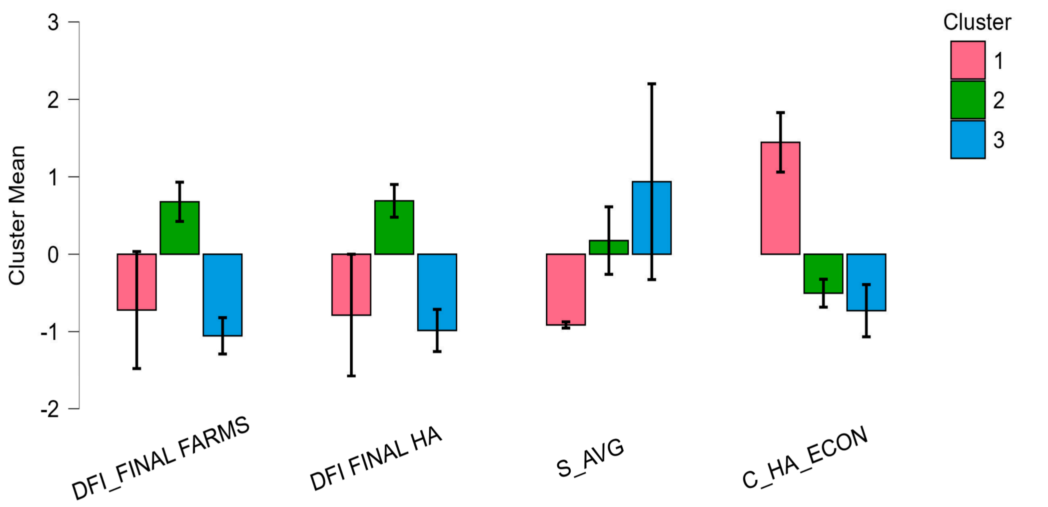

Figure 3. Standardized mean profiles of the three structural clusters identified among the selected EU Member States, based on DFI-Farms, DFI-Hectares, average farm size, and digitalization cost per hectare under the economic scenario.

3.7. Digitalization Costs and Investment Thresholds for the Transition to Agriculture 4.0

To quantify the financial barriers associated with the transition to Agriculture 4.0, a comprehensive analysis of the capital expenditures (CAPEX) required to implement the technologies specific to each dimension of the Digital Farm Index (DFI) was conducted. Financial data collection relied on a mixed approach to ensure accuracy and anchoring in regional economic reality. Thus, official reference prices from the database of the Romanian Agency for Rural Investment Financing (AFIR), used to validate European-funded projects, were integrated alongside current AgriTech market offers from major global providers, indexed to 2026 values.

To reflect the diversity of agricultural holdings and varying levels of technological complexity, the prices of equipment, hardware systems, and software licenses were structured into three investment scenarios: Economic Scenario: Represents the minimum entry barrier, including basic technologies, retrofit solutions, or equipment designed for small farms. Cost-Efficient Scenario: Reflects an optimal price-to-performance ratio, dominated by professional equipment intended for medium-sized commercial farms, aiming for partial automation and network-level integration. Performance Scenario: Illustrates the maximum capital barrier, specific to industrial, high-precision, and fully autonomous systems.

Methodological note on cost aggregation (Modular Average Cost): In the process of consolidating financial data for DFI modeling, the representative barrier for each main pillar (Connectivity, Precision Agriculture, Robotics, and FMIS) was not calculated as a gross sum of all listed equipment. Such an approach would distort economic reality by erroneously simulating a simultaneous purchase of all hardware solutions on the market. Instead, the Modular Average Cost method was applied, determined by the arithmetic mean of the technological subcomponents within each pillar. This methodological decision normalizes the index and accurately reflects the reality of on-the-ground technological adoption: digitalization is an incremental, modular process in which the farm successively integrates specific equipment. Therefore, the capital barrier represents the average financial effort required to implement a new technological stage.

The structural transition toward a fully digitized holding mandatorily begins with securing a stable network infrastructure. The first analyzed dimension, Connectivity, represents the indispensable technical foundation without which real-time data flows cannot be ensured. This dimension covers external internet access (including broadband satellite connections), industrial wireless local area networks (WLAN) for the farm premises, IoT routers for sensor networks, as well as M2M and high-precision satellite correction systems (RTK). The estimated costs for these providers are summarized in Table 5.

Table 5. Synthesis of capital expenditures (CAPEX) for the farm's Connectivity infrastructure. Values represent the estimated averages for implementing specific precision agriculture technological modules.

Technical Component	Analyzed Providers	Data Source	Economic Scenario €	Cost-Efficient Scenario €	Performance Scenario €
1. WAN (External Access)	Starlink, Huawei, Vodafone, Orange	AFIR/Market 2026	437	723	1617
2. LAN/WLAN (Internal Network)	Ubiquiti, Mikrotik, Cisco, TP-Link	Market 2026	219	549	1245
3. LPWAN and Iot	iMETOS, Kerlink, Dragino, MultiTech	AFIR/Market 2026	351	670	1509
4. RTK (Base Stations/GNSS)	Trimble, John Deere, Topcon, Leica	AFIR/Market 2026	2114	6442	12,007
5. M2M (Machinery Telemetry)	Farmtrack, Teltonika, Geotab, Claas	AFIR/Market 2026	997	2249	3875
6. IT Security and Redundancy	Fortinet, Palo Alto, APC, CyberPower	Market 2026	371	951	2814
Representative Barrier (Mean)			748	1931 €	3844 €

Once the connectivity infrastructure is operational, the farm acquires the capacity to digitize technological flows directly in the field through the acquisition of specific hardware for Precision Agriculture. This second dimension operationalizes the active collection of eco-climatic data and the differentiated execution of agricultural operations across parcels. The assessment includes professional agrometeorological stations with auxiliary sensors, probes for monitoring soil water and nutrient dynamics, assisted guidance and hydraulic auto-steering kits, ISOBUS task controllers for Variable Rate Technology (VRT), as well as smart digital traps for integrated pest management (IPM). The detailed structure of these capital costs is presented in Table 6.

Table 6. Synthesis of capital expenditures (CAPEX) for the Precision Agriculture dimension. The assessment covers field monitoring and execution hardware.

Technical Component	Analyzed Providers	Data Source	Economic Scenario €	Cost-Efficient Scenario €	Performance Scenario €
1. Agrometeorological Stations	iMETOS, Teraseya, Davis Instruments, Sencrop, Arable, Pessl Instruments, Meteoblue	AFIR/Market 2026	736	1847	8657
2. Soil Sensors and Probes	CleverFarm, Sentek, CropX, Teralytic, Step Systems, AquaCheck, Decagon	AFIR/Market 2026	587	1409	2569
3. Guidance and Auto-Steering	Trimble, FieldBee, Sveaverken, Topcon, John Deere, CHCNAV, Leica	AFIR/Market 2026	1944	5438	9622
4. VRT and ISOBUS Technologies	Topcon, Trimble, John Deere, Müller-Elektronik, Raven, Kverneland, Ag Leader	AFIR/Market 2026	2271	6618	11,436
5. Smart Traps (IPM)	iMETOS, Teraseya, SysAgria, Trapview, Semios, Bosch Ag, Trap-Eye	AFIR/Market 2026	1443	4207	9214
Representative Barrier (Mean)			1396	3904	8300

While precision agriculture adds digital modules and sensors to conventional agricultural machinery, the Robotics and Advanced Automation dimension marks a profound socio-technological paradigm shift by introducing autonomous cyber-physical systems. This conceptual pillar includes specialized agricultural drones (used for both high-resolution multispectral mapping and ultra-localized application of phytosanitary treatments) and autonomous terrestrial robots capable of executing heavy sowing tasks, mechanical weeding with artificial intelligence detection, or laser weed control. Economically, this pillar represents the steepest leap in capital intensity (CAPEX), generating severe thresholds of technological indivisibility, as observed in Table 7.

Table 7. Synthesis of capital expenditures (CAPEX) for the Robotics and Advanced Automation dimension.

Technical Component	Analyzed Providers	Data Source	Economic Scenario €	Cost-Efficient Scenario €	Performance Scenario €
1. Agricultural Drones	CARGUARD, DJI Agras, XAG, Hylio, EFT, Joyance, TTA, Parrot Ag	AFIR/Market 2026	7816	14,538	22,188
2. Terrestrial Autonomous Robots	GARFORD, FarmDroid, Naïo Technologies, Ecorobotix, Carbon Robotics, AgXeed, Small Robot Co., Burro	AFIR/Market 2026	75,106	130,449	197,164
Representative Barrier (Mean)			41,461	72,493	109,676

However, massive investments in hardware components and autonomous machine fleets become suboptimal in the absence of a centralized platform capable of integrating, processing, and leveraging the heterogeneous information flows generated on the farm.

For this reason, the intangible dimension of digitalization is represented by the FMIS (Farm Management Information Systems) pillar. These software platforms and agricultural ERP systems act as a central decision-making core, unifying agronomic, telemetric, logistical, and financial data to transform them into profitability indicators and managerial forecasts. The annual licensing and implementation costs specific to these software solutions are structured in Table 8.

Table 8. Synthesis of capital and licensing costs for Farm Management Information Systems (FMIS).

Technical Component	Analyzed Providers	Data Source	Economic Scenario €	Cost-Efficient Scenario €	Performance Scenario €
1. Software Platforms (ERP/FMIS)	FieldView, John Deere Ops, xFarm	AFIR/Market 2026	3.288	6.946	13.015
Representative Barrier (Mean)			3.288	6.946	13.015

As evident from the aggregation of the modular assessments presented above, the minimum baseline configuration for a functional digital ecosystem (Economic Scenario) totals €46,893. Upgrading to a configuration optimized for the Cost–Benefit ratio (Cost-Efficient Scenario) raises the initial investment threshold to €85,274, while an advanced integration focused on robotic autonomy and top-tier analytical systems (Performance Scenario) requires a total capital commitment of €134,835. These figures demonstrate that transitioning to Agriculture 4.0 entails a massive immobilization of funds, acting as a severe entry barrier for holdings lacking substantial economies of scale.

To analyze how these fixed capital thresholds influence economic sustainability at the micro level, it is necessary to report them directly to the physical size of the utilized agricultural areas. Table 9 summarizes these total digitalization costs and the corresponding annual depreciation values per hectare for the 18 analyzed Member States, highlighting profound structural asymmetries regarding the capacity to absorb and recoup technological investments.

When costs are reported per average farm area, substantial differences emerge among Member States. In the economic scenario, the cost of digitalization ranges from €77/ha in Slovakia and €99/ha in Czechia to €1221/ha in Greece and €1206/ha in Cyprus. In the efficiency scenario, the range extends from €140/ha in Slovakia and €181/ha in Czechia to €2221/ha in Greece and €2193/ha in Cyprus. In the performance scenario, unit costs range from €222/ha in Slovakia and €286/ha in Czechia to €3512/ha in Greece and €3,467/ha in Cyprus. These differences show that the same technology package generates very different investment burdens depending on the national agricultural structure (Table 10).

The same logic is reflected in the annual depreciation values per hectare. In the economic scenario, depreciation ranges from €15.44/ha in Slovakia and €19.86/ha in Czechia to €244.28/ha in Greece and €241.16/ha in Cyprus. In the efficiency scenario, the range extends from €28.08/ha to €444.22/ha, and in the performance scenario from €44.40/ha to €702.40/ha. These results show that not only the initial cost of digitalization but also the economic sustainability of the payback period differs considerably between countries with consolidated farms and those with more fragmented structures (Table 11).

A comparative analysis between Western and Eastern Europe reveals a significant structural difference in the average size of commercial farms. In the sample analyzed, the average is 110.19 ha in Western Europe and 306.07 ha in Eastern Europe. As a result of this scale difference, digitalization costs per hectare are lower in the Eastern group: €153.21/ha compared to €425.56/ha in the economic scenario, €278.61/ha compared to €773.88/ha in the efficiency scenario, and €440.54/ha compared to €1223.66/ha in the performance scenario. These results show that the economic benefit of digitalization is closely linked to farm size.

Table 9. Investment scenarios, digitalization cost per hectare and annual amortization across the selected EU Member States.

Country	Average Farm Size (ha)	Economic Scenario (€/ha)	Cost-Efficiency Scenario (€/ha)	Performance Scenario (€/ha)	Economic Amortization (€/ha)	Cost-Efficiency Amortization (€/ha)	Performance Amortization (€/ha)
Austria	55.35	879	1599	2582	175.81	319.70	505.51
Belgium	60.73	772	1404	2220	154.44	280.85	444.08
Croatia	136.17	344	626	900	68.87	125.25	198.04
Cyprus	38.89	1206	2193	3457	241.16	438.54	693.42
Czechia	472.33	99	181	286	19.86	36.12	57.11
Estonia	448.38	105	190	301	20.92	38.04	60.14
France	119.21	393	715	1131	78.67	143.06	226.21
Finland	125.63	373	679	1073	74.66	135.76	214.66
Germany	138.45	339	616	974	67.74	123.18	194.78
Greece	38.49	1221	2221	3512	244.28	444.22	702.40
Ireland	103.09	455	827	1308	90.98	165.44	261.59
Hungary	238.07	197	358	566	39.39	71.64	113.27
Latvia	406.73	115	210	332	23.06	41.93	66.30
Netherlands	48.59	965	1755	2775	193.01	350.99	554.99
Portugal	140.86	333	605	957	66.58	121.08	191.45
Romania	368.38	127	231	366	25.46	46.30	73.20
Slovakia	607.36	77	140	222	15.44	28.08	44.40
Sweden	201.78	232	423	668	46.48	84.52	133.65

Notes: All scenarios are based on the same total investment package, expressed in 2026 EUR. The total CAPEX equals EUR 46,893 for the economic scenario, EUR 85,274 for the cost-efficiency scenario, and EUR 134,835 for the performance scenario.

Table 10. Cost of digitalization per hectare in Western and Eastern Europe.

Western Europe (Average: 110.19 ha)	Eastern Europe (Average: 306.07 ha)	Regional Gap: West vs. East
Economic: 425.56 €/ha	Economic: 153.21 €/ha	Economic Gap: 272.35 €/ha
Efficiency: 773.88 €/ha	Efficiency: 278.61 €/ha	Efficiency Gap: 495.27 €/ha
Performance: 1223.66 €/ha	Performance: 440.54 €/ha	Performance Gap: 783.12 €/ha

Table 11. Annual digitalization amortization per hectare over a five-year depreciation horizon.

Western Europe	Eastern Europe	Regional Gap: West vs. East
Economic: 105.37 €	Economic: 57.98 €	Economic Gap: 47.39 €
Efficiency: 191.62 €	Efficiency: 105.45 €	Efficiency Gap: 86.17 €
Performance: 302.99 €	Performance: 166.74 €	Performance Gap: 136.25 €

The cost analysis supports the relevance of the concept of technological indivisibility. Minimum investment thresholds are relatively independent of farm size, while the unit cost of adoption depends decisively on the area over which these fixed costs can be spread. Consequently, large farms and consolidated agricultural systems are better positioned to absorb digital technologies, while small or fragmented farms face a higher investment burden. From this perspective, the economic feasibility of the transition to Agriculture 4.0 depends on the interaction between CAPEX, agricultural structure, and amortization capacity per unit of area.

3.8. Analysis of Linear Associations: Economies of Scale, Cost Barriers, and the Regional Paradox

Prior to the multivariate modeling of determining factors, a Pearson correlation analysis was conducted to assess the direction and strength of linear associations between the dimensions of digital maturity, agricultural structure, and investment effort. The results, summarized in Table 12, highlight several structural relationships relevant to the interpretation of European disparities.

Table 12. Pearson correlation matrix for the analyzed variables (N = 18).

Variable	1. DFI-Farms	2. DFI-Hectares	3. Region (West = 1)	4. S_{avg}	5. C_{ha_econ}
1. DFI-Farms	1				
2. DFI-Hectares	0.990 ***	1			
3. Region (West = 1)	0.439 *	0.407	1		
4. Average area (S_{avg})	0.090	0.133	−0.575 **	1	
5. Cost per hectare (C_{ha_econ})	−0.463 *	−0.515 **	0.187	−0.765 ***	1

Note: level of statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

The two variants of the composite index, DFI-Farms and DFI-Hectares, are almost perfectly positively correlated (r = 0.990, $p < 0.001$), which confirms the internal consistency of the measurement of digital maturity at both the level of economic units and the level of cultivated areas.

A strong and significant negative relationship is also observed between the average area of commercial farms (S_{avg}) and the cost of digitalization per hectare in the economic scenario (C_{ha_econ}) (r = −0.765, $p < 0.001$). This result clearly supports the existence of economies of scale: as the average farm size increases, the unit cost of digitalization decreases, which improves the economic feasibility of the investment.

At the same time, the cost per hectare is negatively correlated with both DFI-Hectares (r = −0.515, p = 0.029) and DFI-Farms (r = −0.463, p = 0.053). These relationships indicate that higher investment burdens tend to be associated with lower levels of digital maturity, especially in the case of agricultural land. The result is consistent with the hypothesis that CAPEX-type entry barriers directly affect the pace of digital technology adoption.

The analysis also reveals a significant negative relationship between the regional variable West = 1 and the average farm size (r = −0.575, p = 0.013), indicating that eastern states tend to have, on average, larger commercial farms. However, the relationship between belonging to the Western group and digital maturity at the farm level is positive (r = 0.439, p = 0.068), suggesting the existence of a regional advantage that cannot be explained solely by farm size. This result justifies the use of multiple regression to simultaneously assess the structural effects of farm size and regional context.

3.9. Structural Determinants of Digitalization: Multiple Linear Regression Modeling

To assess the simultaneous effect of the average size of commercial farms and regional affiliation on digital maturity, two multiple linear regression models were estimated. The analysis aims to evaluate the role of economies of scale and the regional context in explaining DFI variations among the analyzed Member States.

The results for the two dimensions of the Digital Farm Index are summarized in Table 13. Both models are statistically significant and explain a significant proportion of the variation in digital maturity at the European level. For DFI-Hectares, the model yields an Adjusted R^2 = 0.410 and an F-value = 6.918, while for DFI-Farms, Adjusted R^2 = 0.389 and F = 6.411. These results indicate that a significant portion of the variation across countries can be explained by combining information on farm size and belonging to the western or eastern regional context.

Table 13. Multiple regression models for the predictability of digital maturity (N = 18).

Predictors (Independent Variables)	DFI-Hectares (β)	DFI-Farms (β)
Farm Size (ln S_{avg})	0.624 ** (B = 15.73)	0.576 * (B = 13.60)
Geographic Location (West = 1)	0.681 ** (B = 29.86)	0.692 ** (B = 28.46)
Constant (Intercept)	−39.84	−34.45
Adjusted R^2	0.410	0.389
F-value	6.918 **	6.411 *

Note: The table reports standardized coefficients (β), with unstandardized coefficients (B) in parentheses. Significance level: * $p < 0.05$; ** $p < 0.01$.

Both models are statistically significant, explaining a considerable proportion of the variation in digital maturity at the European level (Adjusted R^2 between 0.38 and 0.41). The prediction equations derived from the two models are as follows:

$$\text{DFI-Hectares} = -39.84 + 15.73 \times \ln(S_{avg}) + 29.86 \times \textit{Western\_Region} \quad (5)$$

$$\text{DFI-Farms} = -34.45 + 13.60 \times \ln(S_{avg}) + 28.46 \times \textit{Western\_Region} \quad (6)$$

The standardized coefficients (β) show that, for DFI-Hectares, the effect of regional affiliation (β = 0.681) is slightly stronger than that of farm size (β = 0.624). The result indicates that the digitalization of agricultural land depends both on the benefits of economies of scale and on structural differences among the regional environments in which farms operate.

In the case of DFI-Farms, the regional variable remains the dominant predictor (β = 0.692), while the influence of average farm size is slightly weaker (β = 0.576). This configuration indicates that, at the level of agricultural economic units, the regional context plays a more pronounced role than farm size. In other words, the likelihood that a farm will achieve a higher level of digital maturity appears to depend not only on scale but also on the quality of the regional support ecosystem, including infrastructure, incentive policies, access to financing, and technology transfer capacity.

Overall, the modeling indicates that digitalization is not determined by a single factor, but by the interaction between the agricultural structure and the regional environment. Although the independent *t*-tests did not validate an absolute divide, the regression results suggest the potential existence of a systemic advantage associated with Western countries, which persists even after controlling for average farm size.

3.10. Visual Analysis of Distributions and Structural Gaps

The trends revealed by the statistical analyses are further illustrated through Raincloud plots, which are used to visualize the regional distributions of digital maturity. In line with the analytical strategy described in Section 2.5, Raincloud plots enable the simultaneous examination of distribution density, value dispersion, and the positioning of individual observations.

A comparative analysis of regional distributions (Figure 4) highlights a notable structural paradox. Although Eastern European countries benefit, on average, from larger commercial farms, this land-based advantage does not automatically translate into a higher level of digital maturity or a more homogeneous distribution of technology adoption. For both indicators analyzed—DFI-Hectares and DFI-Farms—the group of Western countries exhibits a more compact distribution and is positioned in the upper range of the digital maturity scale. This profile suggests the existence of an investment, institutional, and technological framework that is more conducive to adoption.

https://doi.org/10.3390/agriculture16141565

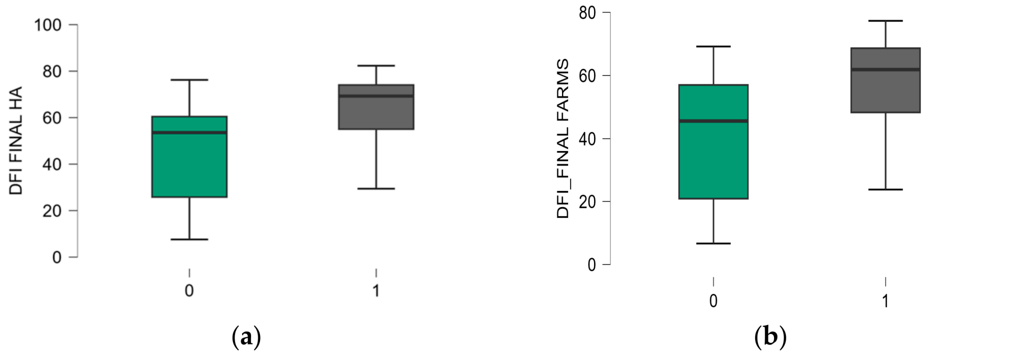

Figure 4. Regional distribution of digital maturity across Eastern and Western European countries. Raincloud plots show the distribution of DFI-Hectares (**a**) and DFI-Farms (**b**) by macro-region. Region 0 denotes Eastern European countries, while Region 1 denotes Western European countries.

Specifically, the distributions for Western countries indicate not only higher average values but also higher minimum thresholds of digitalization, pointing to a lower level of systemic vulnerability. In contrast, the Eastern group exhibits a more heterogeneous and dispersed distribution, reflecting a more uneven digital transition across countries. This variability suggests that, in the absence of a comparable support ecosystem, digitalization depends to a greater extent on structural conditions and individual investment capacity.

4. Discussion

The study's findings show that the digitalization of European agriculture does not follow a uniform model, but rather reflects a process that is highly diverse in structural, economic, and managerial terms. In line with the literature defining Agriculture 4.0 as a transition toward data-intensive agriculture, interconnectivity, and digitally assisted decision-making, digital transformation must be understood not as a mere adoption of equipment, but as a reorganization of the farm's productive and managerial functions [7,8,10,26]. From this perspective, the combination of bibliometric analysis, the construction of the DFI index, and cost modeling allows for an integrated interpretation of digitalization, moving beyond approaches that treat infrastructure, adoption, or economic performance separately.

4.1. Consolidating the Digitalization of Agriculture as a Research Field and the Relevance of the DFI Architecture

The bibliometric analysis highlights the rapid maturation of agricultural digitalization as a distinct interdisciplinary field, centered on the relationship between precision agriculture, remote sensing, artificial intelligence, management systems, and sustainability. This finding is consistent with the literature describing agricultural digitalization as a socio-technical architecture in which productive, informational, and organizational processes are increasingly integrated [7–10]. The centrality of the term "precision agriculture" in the co-occurrence network and the positioning of thematic clusters oriented toward management, systems, IoT, and productivity support the selection of the four pillars of the DFI index: connectivity, precision agriculture, robotics, and FMIS.

From this perspective, the DFI is not merely a composite indicator of adoption, but a synthesis of recurring themes in the contemporary literature on agricultural digitalization. This result is significant because it addresses a common limitation of studies on Agriculture 4.0, namely the analytical fragmentation of technologies. As recent literature on the economics of AI-based digital technologies also highlights, the economic and organizational value of digitalization does not stem from the isolated presence of a technological solution, but from farms' ability to integrate hardware, software, and analytical components into a coherent functional system [53]. In this vein, the DFI framework is supported both bibliometrically and conceptually.

4.2. Uneven Digital Maturity and Concentration of Adoption in Dominant Farms

Results based on DFI-Farms and DFI-Hectares show that digital maturity is more pronounced at the level of cultivated area than at the level of the number of farms, suggesting that digital technologies are adopted primarily by dominant commercial farms. This observation is consistent with the literature showing that the adoption of digital and precision technologies is strongly influenced by farm size, capitalization capacity, educational level, and access to infrastructure and support services [24,26,54–56]. Therefore, the difference between DFI-Farms and DFI-Hectares should not be interpreted merely as a statistical variation, but as an expression of a selective concentration of the digital transition.

This interpretation is also supported by recent studies showing that digital adoption often follows a sequential and cumulative logic, in which farms progressively enter the digitalization process, combining technologies based on their absorption capacity and perception of economic benefits [57]. At the same time, the literature confirms that small and medium-sized farms are more exposed to financial, informational, and organizational barriers, which makes adoption slower and more fragmented [56,58]. From this perspective, the results make an important contribution by showing not only who is adopting, but also where digitalization is actually concentrated within the European agricultural structure. The dual index explicitly captures this polarization: DFI-Farms exposes the low degree of technology democratization at the grassroots level, while DFI-Hectares reveals how a narrow segment of highly capitalized farms mathematically inflates the territorial coverage of Agriculture 4.0.

4.3. Economies of Scale and Technological Indivisibility as Key Explanatory Mechanisms

A key finding of the study, supported by multiple linear regression modeling, is that the economic feasibility of digitalization depends on a dual mechanism: farm size, which allows for the efficient absorption of fixed costs, and membership in a more robust regional ecosystem. The negative relationship between average farm size and the cost of digitalization per hectare supports the relevance of the concept of technological indivisibility, consistent with recent economic literature highlighting that digital technologies tend to entail high barriers to entry [37,59].

The scientific novelty of this study lies in separating the scale effect from the regional effect. The results suggest the existence of a structural East–West paradox: although Eastern European countries possess a scale advantage, reflected in larger commercial farms, this advantage is not sufficient to achieve the levels of digital maturity observed in Western Europe. However, this contrast should be interpreted with methodological caution. The independent-samples *t*-tests did not provide statistically significant support for H1 at the conventional 5% threshold, although the direction of the differences and the medium-to-large effect sizes indicate practically relevant disparities between Western and Eastern EU Member States. Therefore, H1 should be considered only partially supported. This interpretation is also consistent with comparative evidence on the Romanian crop sector, which highlights persistent structural differences between Romania and more consolidated EU agricultural systems [35]. The multiple linear regression results further indicate that, at the level of farm adoption, the regional ecosystem ($\beta = 0.692$) has a stronger influence than farm size ($\beta = 0.576$). This supports the interpretation that Western countries benefit from a systemic advantage associated with a more favorable institutional, educational, and investment environment, capable of reducing the impact of the investment thresholds of digitalization. In this regard, the findings extend previous observations on the profitability of technologies [15,60,61], showing that farm-size structure functions as a facilitator, while the regional ecosystem acts as a major catalyst for the transition to Agriculture 4.0.

4.4. The Hardware–Software Paradox and the Gap Between Technological Adoption and Managerial Maturity

To fully understand these results, it is essential to establish a clear conceptual distinction between three distinct stages of agricultural modernization: (1) technology availability (the existence of solutions on the market); (2) technology adoption (the actual acquisition of hardware and equipment, heavily constrained by CAPEX barriers); and (3) effective management use (true digital transformation). The mere act of adopting precision equipment does not equate to a successful digital transformation, nor does it guarantee an automatic improvement in farm performance. True economic value is unlocked only in the third stage, when the data generated by the hardware are analytically integrated through Farm Management Information Systems (FMIS) to substantiate agronomic decisions.

Another important finding is the gap between the operational dimension of digitalization and the managerial integration of data, as evidenced by lower levels of FMIS adoption relative to connectivity, precision agriculture, or robotics in many countries. This finding is consistent with the literature on the hardware–software paradox, according to which technological modernization often progresses more rapidly through the acquisition of tangible equipment and systems than through the software, organizational, and managerial integration of information flows [31,32].

The results are also supported by recent literature, which shows that the transition from fragmented records to comprehensive digital systems is hampered by persistent issues of interoperability, data completeness, and integration between technical and economic modules [62]. Furthermore, the literature on digital knowledge and decision support systems shows that the true value of digitalization emerges only when the collected data is transformed into operational knowledge and contextualized managerial decisions [63]. From this perspective, the study confirms that digital maturity cannot be assessed solely by the farm's technical equipment, but rather by the level of functional integration between the digital infrastructure, operational use, and the managerial capacity to transform data into economic decisions.

This observation also has an important human dimension. The literature shows that the level of digital skills, trust in technology, and familiarity with IT tools have a decisive influence on farms' ability to move from adopting technology to actually using it in management [21,58,64]. Consequently, the gap between equipment adoption and managerial maturity is not merely a matter of technological supply, but also one of human capital and the organization of the decision-making process.

Furthermore, it is crucial to recognize that while this study methodologically isolates Capital Expenditures (CAPEX) to quantify the initial entry barrier of technological indivisibility, the financial burden of digitalization extends much further. The Total Cost of Ownership (TCO) for Agriculture 4.0 also includes substantial Operational Expenditures (OPEX), such as annual software licensing, sensor maintenance, data services, and specialized consulting fees. Financial capital alone does not guarantee successful adoption. The transition is inherently constrained by socio-demographic and institutional barriers, including the aging of the farming population, a lack of advanced digital skills, the inconsistent quality of rural internet connectivity, and limited access to dedicated credit lines. Therefore, while CAPEX determines the structural capacity to acquire technology, OPEX and the broader institutional support network determine the farm's ability to utilize it sustainably.

https://doi.org/10.3390/agriculture16141565

4.5. Implications for Public Policy and a More Inclusive Digital Transition

The results have direct implications for European agricultural and digital policies. In the absence of differentiated support mechanisms, digitalization risks exacerbating the structural polarization between large and small farms. High fixed costs, uneven digital infrastructure, limited skills, and difficult managerial integration can turn the digital transition into a selective, rather than an inclusive, process. This conclusion is consistent with studies showing that the most persistent barriers to adoption are not only technical, but also economic, organizational, and cognitive [21,23,26,54,55,58].

The literature supports the idea that digitalization policies must go beyond subsidizing hardware and simultaneously address infrastructure, skills, interoperability, and decision support [54,56,58,65]. From this perspective, the results—consistent with the systemic advantage of well-established regional ecosystems—suggest that a fair digital transition in European agriculture requires differentiated interventions. For some Eastern European countries, where institutional support infrastructure and technology transfer mechanisms appear less established, public interventions should move away from exclusive CAPEX grants. Instead, policies should focus heavily on developing technology transfer networks, supporting European Digital Innovation Hubs (EDIHs) tailored to the agri-food sector [66], and creating accessible, interoperable FMIS solutions optimized for small and medium-sized commercial farms.

To ensure an efficient transition, European and national public policies must abandon 'one-size-fits-all' approaches and implement differentiated strategies, tailored to the specific needs of the various country groups and agricultural structures identified in this study:

A. For fragmented agricultural systems with major CAPEX barriers (e.g., Greece, Cyprus, and smallholdings in Central Europe): Individual machinery subsidies are inefficient due to high amortization barriers (technological indivisibility). For these structures, policies must stimulate shared access models. We recommend prioritizing the funding of 'machinery rings', digital cooperatives, and incentivizing the provision of Technology-as-a-Service (TaaS). This approach allows small farms to benefit from precision agriculture without bearing the financial risk of unsustainable fixed investments.

B. For systems with economies of scale but low FMIS adoption (e.g., Romania, Slovakia): This category faces a 'hardware-software paradox,' where large farms acquire modern machinery but fail to integrate it managerially. In this case, policies should condition the provision of equipment grants (CAPEX) on participation in digital skills training programs. Furthermore, it is necessary to introduce subsidies for operational expenditures (OPEX), such as innovation vouchers covered by eco-schemes, exclusively dedicated to purchasing software licenses (SaaS) and data-driven agronomic consulting services.

C. For digitally advanced systems (e.g., Finland, France, Ireland): In countries where adoption levels are already high, state intervention must shift from stimulating acquisitions to ensuring data governance. Recommendations for this group aim at legislating mandatory interoperability standards (to prevent vendor lock-in), enhancing farm cybersecurity, and developing an open European agricultural data space to enable the sharing and predictive use of data at the macro-territorial level.

4.6. Macroeconomic, Geopolitical, and Socio-Demographic Constraints

Beyond structural and technological barriers, the transition to Agriculture 4.0 is heavily constrained by contemporary geopolitical and macroeconomic shocks. The ongoing Russia-Ukraine war has fundamentally altered the European agricultural market by triggering massive input cost shocks, particularly in energy, natural gas, and synthetic fertilizers. This has severely compressed farm operating margins across the EU. Within the context of our study, this prolonged crisis acts as a major macroeconomic constraint: by draining liquid capital reserves, it elevates the ex-ante capital entry barrier (CAPEX) for digital technologies, forcing farmers to prioritize short-term survival over long-term structural digitalization.

Simultaneously, global trade protectionism, such as U.S. tariffs on European imported goods, introduces high systemic volatility into agri-food supply chains, directly threatening perishable product sectors that rely on rapid, frictionless export corridors. Macro-welfare losses driven by such tariff barriers necessitate aggressive microeconomic cost optimization. Consequently, farm-level digitalization (such as precision agriculture and smart supply chain tracking) ceases to be a luxury and becomes an absolute necessity to offset external trade shocks and protect domestic sector welfare.

Looking forward, the accelerated integration of Artificial Intelligence (AI) and autonomous robotics will fundamentally reshape the European agricultural labor market. In European agriculture, AI is shifting the labor paradigm from manual substitution to structural transformation. Rather than inducing negative mass unemployment, AI adoption primarily addresses the chronic and severe rural labor shortages and aging demographics plaguing the EU agricultural sector. However, it does create a polarization risk: replacing low-skilled physical labor while exponentially increasing the demand for highly skilled managerial labor capable of interpreting data (reflecting the core of our hardware-software paradox). To mitigate demographic drainage and ensure a just transition, public policy must pivot from merely subsidizing physical machinery (CAPEX) toward funding digital literacy via Agricultural Knowledge and Innovation Systems (AKIS), coupled with targeted rural infrastructure development.

4.7. The Study's Contribution

By combining bibliometric analysis with a comparative measurement of digital maturity and modeling of implementation costs, the study makes a distinct contribution to the literature on agricultural digitalization. Unlike studies that address *ex post* adoption or analyze a single category of technology in isolation, this article proposes an integrated understanding of digitalization as a multidimensional and structurally conditioned process. In this sense, the DFI functions not only as a descriptive tool but also as a bridge between the literature on Agriculture 4.0 and the economic analysis of investment feasibility.

This paper makes a contribution structured around three key dimensions. Methodologically, it proposes the DFI as a multidimensional composite tool for assessing digital maturity at the farm and agricultural area levels. Empirically, it provides a comparative assessment of digitalization and implementation costs across 18 European Union member states. Theoretically, it conceptualizes agricultural digitalization as an investment characterized by technological indivisibility, fixed costs, and dependence on the regional adoption context. This perspective provides a useful framework for explaining European heterogeneity and for understanding why the adoption of digital technologies remains profoundly uneven among agricultural systems facing the same general pressures for modernization.

5. Conclusions

This study shows that the digitalization of European agriculture is an uneven process, shaped by structural, economic, and institutional mechanisms. By combining bibliometric analysis with an empirical assessment of digital maturity and modeling of implementation costs, the research argues that digitalization should be understood as the functional integration of connectivity, precision agriculture, robotics, and FMIS. The results indicate a concentration of Agriculture 4.0 technology adoption in dominant commercial farms, with the area-weighted indicator (DFI-Hectares) consistently exceeding the adoption level reported per economic unit (DFI-Farms).

The study's major scientific contribution lies in its dual modeling of the determinants of digitalization, by separating the effect of economies of scale from that of regional ecosystems. The analysis of costs per hectare supports the relevance of technological indivisibility, showing that land fragmentation can turn innovation into a significant barrier to investment. At the same time, the West–East divide in agricultural digital maturity should be interpreted cautiously. Although Western Member States recorded higher average values for both DFI-Farms and DFI-Hectares, these differences were not statistically significant at the 5% level; therefore, H1 is only partially supported. Nevertheless, the observed differences and effect sizes suggest a relevant practical divergence between Western and Eastern EU Member States. Multiple linear regression further highlights a structural paradox: although Eastern European countries have, on average, larger commercial areas—which mathematically reduces the fixed cost per hectare—they do not reach the levels of digital maturity observed in Western Europe. The results show that while farm size is an important predictor of territorial digitalization ($\beta = 0.624$), belonging to a consolidated regional ecosystem appears to be a stronger predictor of adoption at the farm level ($\beta = 0.692$).

This dynamic is consistent with the existence of a systemic advantage for Western European farmers, associated with a more favorable institutional environment, better-calibrated support instruments, and more mature technology transfer networks. At the same time, the results highlight the existence of a hardware–software imbalance, in which the adoption of advanced equipment is not proportionally accompanied by the managerial integration of data through FMIS solutions.

The main implication for public policy is that simply subsidizing equipment (CAPEX) is not enough to bridge the digital divide in the absence of a supportive ecosystem. Targeted policies should simultaneously address rural infrastructure, data management skills, interoperability, and technology transfer. Without these integrated interventions, digitalization risks functioning not only as a driver of modernization but also as a mechanism that exacerbates competitive polarization among farms and macro-regions within the European Union.

In interpreting these conclusions, certain inherent limitations of the study must be considered. Since the research relies on cross-sectional aggregate data and a sample limited to 18 Member States, the results reflect structural associations and macroeconomic trends, precluding the demonstration of strict causal relationships at the individual level. Furthermore, the modeling of capital expenditures (CAPEX) represents a simplified estimate and simulation of initial investment barriers, which does not fully capture the long-term dynamics of all operational costs (OPEX). Therefore, the claims in this study should not be viewed as an absolute generalization for all of European agriculture, but rather as a grounded starting point for future longitudinal research aimed at exploring the socio-economic complexity of the digital transition in greater depth.

Author Contributions: Conceptualization, C.-O.A. and G.S.; methodology, C.-O.A. and G.S.; software, C.-O.A.; validation, C.-D.D., O.C. and G.S.; formal analysis, C.-O.A. and G.S.; investigation, C.-O.A.; data curation, C.-O.A. and C.-D.D.; writing—original draft preparation, C.-O.A.; writing—review and editing, C.-D.D., O.C. and G.S.; visualization, C.-O.A.; supervision, G.S. and O.C.; project administration, O.C.; funding acquisition, O.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research is part of the North-East Regional Program 2021–2027, contract no. 654/28.03.2025, entitled "Development of an integrated ERP software program for increasing performance in agribusiness through the construction of the Advanced Research Center in Agribusiness–ARCA", MySMIS code 335643, signed between the North-East Regional Development Agency, as managing authority, and Iasi University of Life Sciences, as beneficiary.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: During the preparation of this manuscript, the authors used large language model tools, including Gemini 3.1 Pro and ChatGPT 5.5 Thinking, to support the summarization and synthesis of large bodies of text. The authors reviewed, edited, and validated all AI-assisted outputs and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AFIR	Agency for the Financing of Rural Investments
CAP	Common Agricultural Policy
CAPEX	Capital Expenditure
CPS	Cyber-Physical Systems
DESI	Digital Economy and Society Index
DFI	Digital Farm Index
EU	European Union
FMIS	Farm Management Information Systems
GNSS	Global Navigation Satellite System
IoT	Internet of Things
IPCC	Intergovernmental Panel on Climate Change
IPPI	Industrial Producer Price Index
JASP	JASP Statistical Software
MLR	Multiple Linear Regression
NUTS	Nomenclature of Territorial Units for Statistics
PPI	Producer Price Index
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ROI	Return on Investment
SO	Standard Output
VRT	Variable Rate Technology
WoS	Web of Science

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https://doi.org/10.3390/agriculture16141565