AgriEngineering

Systematic Review

Digital Literacy and Technology Adoption in Agriculture: A Systematic Review of Factors and Strategies

María Arangurí [1,*], Huilder Mera [1], William Noblecilla [1] and Cristina Lucini [2]

[1] Department of Engineering, Catholic University of Santo Toribio de Mogrovejo, Chiclayo 14001, Peru; hmera@usat.edu.pe (H.M.); wnoblecilla@usat.edu.pe (W.N.)
[2] Faculty of Science and Arts, Catholic University of Ávila, 05005 Ávila, Spain; cristina.lucini@ucavila.es
* Correspondence: maranguri@usat.edu.pe; Tel.: +51-968700148

Abstract

This systematic review analyzed a total of 109 scientific articles with the aim of identifying, organizing, and synthesizing academic output related to digital literacy, technology adoption in agricultural sectors, digital skills, and socioeconomic and cultural factors that influence the implementation of emerging technologies. Peer-reviewed academic publications available in open access and written in English were reviewed, complying with the PRISMA protocol guidelines. They came predominantly from Europe, Asia, and Latin America, which allowed for a global perspective. Quantitative, qualitative, and mixed approaches were applied, highlighting the use of surveys, interviews, and bibliometric analysis. Factors affecting the adoption of precision agriculture by smallholder farmers, challenges for the implementation of technologies in rural contexts, and sociocultural barriers to technological innovation were evaluated. The trend focuses on the need for sound public policies, continuous training strategies, technological accessibility, and contextualized approaches to ensure effective technology adoption. In conclusion, a broad and critical overview of the advances, limitations, and challenges surrounding digital literacy and technology adoption is provided as a basis for an in-depth debate on the digital transformation of contemporary agriculture.

Keywords: technological training; bibliometric analysis; technology applied to agriculture; digital literacy; technology adoption

check for updates

Academic Editor: Ray E. Sheriff

Received: 3 July 2025
Revised: 13 August 2025
Accepted: 19 August 2025
Published: 11 September 2025

Citation: Arangurí, M.; Mera, H.; Noblecilla, W.; Lucini, C. Digital Literacy and Technology Adoption in Agriculture: A Systematic Review of Factors and Strategies. *AgriEngineering* **2025**, *7*, 296. https://doi.org/10.3390/agriengineering7090296

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Today, the digital transformation of agriculture represents a strategic axis for addressing the challenges of food security, sustainability, and climate change. This change is driven by the integration of emerging technologies, such as artificial intelligence (AI), the Internet of Things (IoT), machine learning, satellite image analysis, and remote monitoring systems. However, the adoption of these technologies depends not only on their availability but also on the level of digital literacy of farmers, especially in rural areas or among smallholder farmers [1,2].

Agricultural digital literacy involves the ability to understand, use, and apply technological tools to improve productivity, crop monitoring, and decision-making [3]. In the context of rice cultivation, multiple research studies have explored the use of sensors, unmanned aerial vehicles (UAVs), computer vision, neural networks, and smart platforms to optimize fertilization practices, pest control, yield estimation, and disease prediction [4–6].

Although rice features prominently in several of the studies reviewed and was used as a reference in the search strategy to capture representative research, the scope of this review is not limited to this crop. The analyses and conclusions cover other agricultural systems and are applicable in diverse production contexts, given that many of the technologies, models, and strategies identified have characteristics that can be extrapolated to multiple crops.

Despite these advances, significant barriers to the effective adoption of these technologies remain, related to factors such as unequal access to connectivity, insufficient technical training, the generational gap in digital use, and the lack of strategies adapted to local conditions [7,8]. Given this problem, a comprehensive understanding of the factors that facilitate or limit digital literacy and its direct relationship with the adoption of agricultural technologies is required.

In addition, the rapid expansion of AI, computer vision, and data-driven recommendation systems has opened up new possibilities for crop disease management, water needs estimation, and optimization of agricultural input use [9–11]. These technologies are being applied in decision support models that allow, for example, the prediction of irrigation needs or the diagnosis of leaf diseases from UAV images, thus contributing to improving the efficiency and sustainability of production [12]

It is also essential to consider the financial conditions of farms, given that the capacity to invest in artificial intelligence (AI) solutions varies significantly among producers [13,14]. Smaller farms often face budget constraints and have less access to financing, which limits their ability to adopt advanced technologies [12,15]. Furthermore, farm size directly influences the viability and expected return on AI investments, with medium and large farms more likely to have the infrastructure and human resources needed for implementation [8,16]. In this context, it is essential that AI technologies are designed and adapted to the specific needs of each type of producer, ensuring that the proposed solutions are scalable, economically accessible, and relevant to the different agricultural production models present in the study regions [17,18].

In this context, the fusion of machine learning techniques with remote sensing platforms, drones, and IoT platforms has strengthened the application of precision agriculture, particularly in crops such as rice, where decisions based on climatic, edaphic, and phenological variables are required [19,20]. Algorithms, such as convolutional neural networks (CNN), YOLO, and attention networks, have been adapted to detect leaf diseases, identify rice varieties, and estimate the impact of nutritional inputs with a high level of accuracy [21,22].

However, farmers' access to these technologies is conditioned by their ability to understand, interpret, and act on the data generated. Therefore, digital literacy involves not only knowing how to use a tool but also understanding how it works, interpreting the information, and making agricultural decisions based on it [17,23]. This challenge is even greater in rural populations with low connectivity, limited technical training, and limited institutional support, making training strategies, technical support, and the development of intuitive systems essential to closing the digital divide in agriculture.

Despite the growing number of studies on technologies applied to agriculture, there is a notable dispersion in the methodological and thematic approaches used to address digital literacy as a key factor in technology adoption. Many studies focus on technical aspects of digital tools or specific applications, without systematically integrating the human, social, educational, and contextual factors that condition their effective adoption. In addition, there is a gap in the literature regarding integrative reviews that allow for a comprehensive and critical understanding of the phenomenon. In this context, there is a need for a systematic review of the literature that consolidates existing findings, identifies

key research gaps, and proposes strategic lines of action to promote sustainable digital transformation in the agricultural sector.

The overall objective of this study is to analyze the factors that influence digital literacy and its relationship with technology adoption in agriculture, as well as the strategies implemented to improve this process, through a systematic review of recent scientific literature.

To achieve this purpose, six specific objectives were set: (1) to describe the main topics, tools, or technologies addressed in digital literacy by farmers, (2) to identify the tools and techniques used to measure the impact of digital literacy on the adoption of agricultural technology, (3) to analyze the theoretical models and approaches that have been applied to study the adoption of agricultural technologies based on digital literacy, (4) to determine the main factors that influence farmers' digital literacy and its relationship with the adoption of agricultural technologies, (5) to synthesize the main findings and barriers regarding the relationship between digital literacy and the adoption of agricultural technologies reported in the scientific literature; and (6) to examine the strategies implemented to improve farmers' digital literacy and their impact on the adoption of emerging technologies. The interrelationship between the objectives is illustrated graphically in Figure 1.

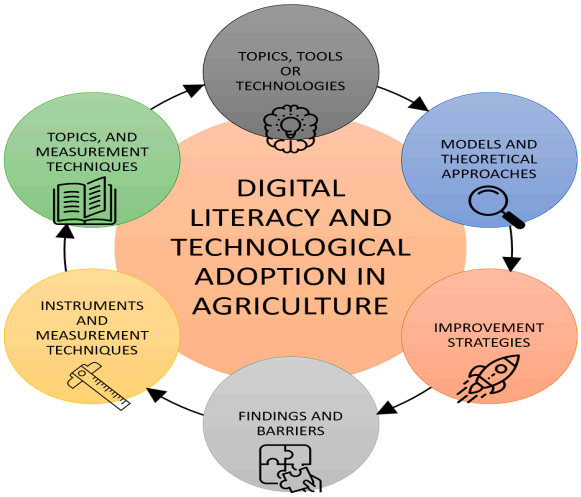


Figure 1. Relationship between specific objectives and their contribution to the overall objective.

This review contributes in three main ways: (1) for the academic community, it establishes a robust conceptual and methodological framework that broadens the understanding of digital literacy and its relationship with technology adoption in agriculture; (2) for public policy formulation, it provides consolidated evidence to support decisions on digital infrastructure, training, and regulation; and (3) for the productive and technological sector, it guides the development of solutions tailored to the real needs and capacities of producers, prioritizing usability, accessibility, and sustainability [24]. In this sense, the article responds to the urgent need to articulate dispersed knowledge within an integrative framework that advances the literature and accelerates the transition toward more inclusive and digitally competent agricultural systems.

2. Materials and Methods

The protocol was registered with PROSPERO on 9 July 2025 (registration number: 125 CRD420251088831) with the last update on 14 August 2025.

2.1. Design of the Systematic Literature Review

This research corresponds to a Systematic Literature Review (SLR), developed under the guidelines of the PRISMA 2020 protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [25]. This approach ensures transparency, traceability, and

rigor in the search, selection, analysis, and synthesis of scientific literature on digital literacy and technology adoption in agriculture. The review included studies on digital literacy applied to farmers, technology adoption, emerging technologies in agriculture, theoretical models, and training strategies.

2.2. Research Questions

The research questions were formulated using the PICO framework:

Population (P): Farmers and their process of technology adoption in agriculture.
Intervention (I): Digital literacy, technology training, training strategies.
Comparison (C): Differences in adoption with and without digital literacy, different theoretical models, and applied strategies.
Outcome (O): Level of technology adoption, influencing factors, effective strategies, existing barriers, and impact on the agricultural sector.

The main question was: What factors influence digital literacy and its relationship with technology adoption in agriculture? From this, specific questions were derived, such as: (1) What topics, tools, or technologies have been addressed in digital literacy processes aimed at farmers? (2) What methodological instruments and techniques have been used to assess the impact of digital literacy on the adoption of agricultural technologies? (3) What theoretical models and analytical approaches have been used to study the relationship between digital literacy and technology adoption in agriculture? (4) What are the main factors influencing farmers' digital literacy and how do they relate to the adoption of agricultural technologies? (5) What findings and barriers are reported in the scientific literature on the relationship between digital literacy and technology adoption in agriculture? (6) What strategies or practices have been implemented to improve farmers' digital literacy and what effects have they had on the adoption of emerging technologies?

2.3. Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were defined with the aim of ensuring the relevance and quality of the studies considered in the review. Articles were included based on the following criteria:

- Published between 2015 and 2025, to capture recent evidence reflecting rapid changes in digital technologies applied to agriculture.
- Written in English, in order to incorporate relevant literature from global contexts.
- Open access (except in IEEE Xplore, where all relevant articles were considered due to limited availability in OA).
- That explicitly addressed digital literacy in agricultural contexts and its relationship to technology adoption.

The following were excluded:

- Articles that were not available in full text.
- Articles that did not refer directly to agricultural contexts.
- Studies not related to digital skills or technology adoption in agricultural contexts.
- Editorials, non-systematic reviews, non-scientific essays, or unrefereed theses.

These criteria were selected in order to maintain methodological rigor and avoid thematic dispersion, ensuring that the articles analyzed provided direct and verifiable information to meet the specific objectives of the study.

2.4. Sources of Information

The scientific databases used for the literature search were:

- Scopus: for its multidisciplinary coverage and editorial rigor.

- ScienceDirect: for its high presence of research in agricultural sciences and technology.
- IEEE Xplore: for its technical focus on engineering, computer science, and emerging technologies.

These three databases allowed us to cover the fields of digital literacy, technology adoption, and precision agriculture in a complementary manner.

Although platforms such as Google Scholar offer a wider range of results, they have less editorial quality control and a greater presence of non-peer-reviewed literature, which could reduce the reliability of the findings. For this reason, databases with high editorial standards and extensive subject indexing were chosen, balancing coverage, relevance, and scientific quality.

2.5. Search Strategy

Specific search strings were developed for each database, taking into account the thematic structure of the study. Key terms were grouped into five broad categories: digital literacy, technology adoption, agricultural technologies, population, and target crop. Boolean operators (AND, OR) were used, and filters were adjusted according to the database.

The inclusion of the term "rice" and its synonyms within the "specific crop" category in the Scopus search string was justified based on the results obtained in the exploratory phase of the review. During this stage, it was identified that a considerable proportion of recent literature on digital literacy and technology adoption in agriculture focused on rice cultivation, especially in regions of Asia and Africa, where this cereal is a strategic pillar of food security and rural development. Rice was used as a model crop because it is the subject of a large number of case studies that integrate emerging technologies (sensors, IoT, UAVs, satellite monitoring, mobile platforms) with training and digital literacy processes. This research provides solid analytical frameworks that can be replicated in other production systems, making it a valuable source for understanding the interaction between technical, socioeconomic, and cultural factors in technology adoption. Therefore, the use of this filter sought to focus the search on empirical studies with high thematic relevance, without implying that the findings and conclusions of the review are limited exclusively to this crop.

In ScienceDirect, the use of operators was limited due to platform restrictions. In IEEE Xplore, all relevant results were accepted without an open access filter to maximize retrieval.

A consolidated table of keywords and synonyms grouped by concept was developed (Table 1), which allowed for the proper structuring of search equations for each database. In addition, the three main search strings used were summarized (Table 2).

Table 1. Keywords and synonyms used in the search.

Thematic Concept	Keywords/Synonyms	Databases Used
Digital literacy	"digital literacy," "digital competence," "ICT skills," "digital education," "e-literacy," "digital skills"	Scopus, IEEE Xplore, ScienceDirect
Technology adoption	"technology adoption," "technology acceptance," "innovation adoption," "technological adoption," "technology dissemination," "awareness raising," "capacity building," "training"	Scopus, IEEE Xplore, ScienceDirect

Table 1. *Cont.*

Thematic Concept	Keywords/Synonyms	Databases Used
Technology applied to agriculture	"agriculture," "precision agriculture," "smart farming," "precision farming," "site-specific agriculture," "agricultural technology," "smart agriculture," "agricultural innovation," "farm management system," "digital transformation," "digitalization," "tools," "applications," "software," "digital farming"	Scopus, IEEE Xplore, ScienceDirect
Subjects (Farmers)	"farmer," "agriculturist," "smallholder farmer," "rural community," "farming sector"	Scopus
Specific crop (rice)	"rice", "rice farming", "rice production", "paddy farming", "paddy cultivation", "rice cropping"	Scopus

Table 2. Search string by database.

Database	Search String
Scopus	TITLE-ABS-KEY ("digital literacy" OR "digital competence" OR "ICT skills" OR "digital education" OR "e-literacy" OR "technology adoption" OR "technology acceptance" OR "innovation adoption" OR "technological adoption" OR "capacity building" OR "awareness raising" OR "technology dissemination" OR "training" OR "digital skills") AND ("technology" OR "tools" OR "applications" OR "digitalization" OR "software" OR "agricultural innovation" OR "precision agriculture" OR "smart farming" OR "digital transformation" OR "farm management system") AND ("farmer" OR "agriculturist" OR "smallholder farmer" OR "rural community" OR "farming sector") AND ("rice" OR "rice farming" OR "rice production" OR "paddy farming" OR "paddy cultivation" OR "rice cropping")
IEEE Xplore	("digital literacy" OR "digital competence" OR "ICT skills" OR "digital education" OR "e-literacy" OR "technology adoption") AND ("agriculture" OR "precision agriculture" OR "smart agriculture" OR "digital farming")
ScienceDirect	("digital literacy" OR "digital competence" OR "ICT skills" OR "e-literacy") AND ("technology adoption") AND ("agriculture" OR "precision agriculture" OR "smart agriculture" OR "digital farming")

2.6. Study Selection Process

The selection of studies was carried out in four phases, in accordance with the PRISMA model:

Identification: A total of 704 records were identified in three databases: Scopus (296), ScienceDirect (273), and IEEE Xplore (135). A total of 12 duplicate records and 248 records were eliminated for not meeting the initial criteria (language, document type, and open access), resulting in 444 records for the screening phase.

Screening: 444 titles and abstracts were reviewed, of which 293 were excluded for thematic irrelevance. The remaining proceeded to the full-text retrieval attempt phase.

Eligibility: Of the 151 studies selected, 25 could not be retrieved. A total of 126 full-text articles were evaluated, of which 17 were excluded because they did not address digital literacy in agriculture (7) or because they did not address the adoption of agricultural technology (10).

Inclusion: Finally, 109 studies met all the criteria and were included in the systematic review: Scopus (72), ScienceDirect (32), and IEEEXplore (5).

The process followed is summarized in Table 3 and shown in the PRISMA diagram in Figure 1.

Table 3. Summary of the PRISMA process in the preparation of the article.

Database	Identified	Screened	Sought for Retrieval	Assessed for Eligibility	Included in Review
Scopus	296	217	76	76	72
ScienceDirect	273	104	45	33	32
IEEE Xplore	135	123	30	17	5
Total	704	444	151	126	109

Zotero software 6.0.36 as used for bibliographic management and Excel for recording inclusion/exclusion decisions. The complete flow of the process was represented by the updated PRISMA diagram in Figure 2.

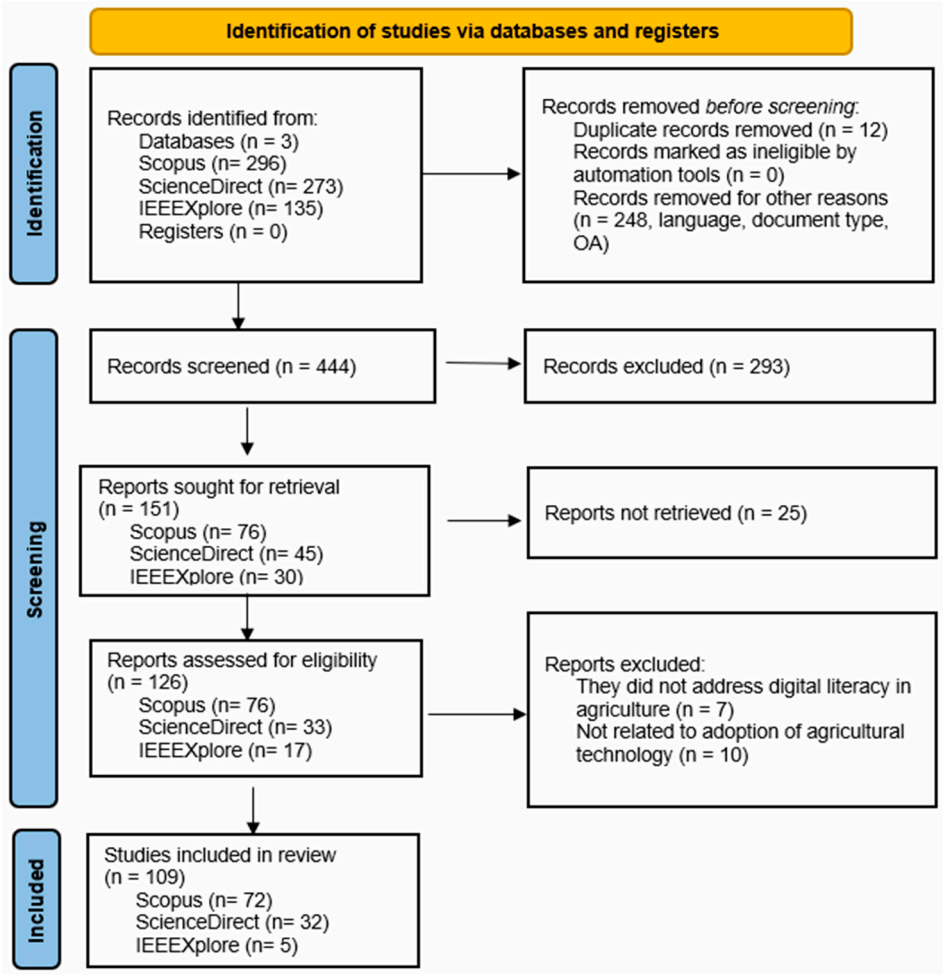


Figure 2. PRISMA diagram summarizing the process.

2.7. Methodological Quality Assessment

The quality of the studies was assessed considering aspects such as clarity in the formulation of the problem, methodological consistency, thematic relevance, and applicability of the results. This review prioritized studies that provided empirical evidence related to digital literacy factors, technology adoption, and models or strategies applied to the agricultural sector.

2.8. Data Extraction

A data extraction form structured in an Excel spreadsheet was used. The fields included: author(s), year of publication, country, type of study, technologies addressed, tools used, theories or models employed (e.g., TAM, UTAUT), target population, instruments applied, influencing factors, strategies, and main results. This procedure allowed the content to be organized and systematized in a comparative and categorical manner.

2.9. Data Synthesis and Analysis

The data were synthesized using a mixed approach, integrating qualitative thematic analysis, descriptive quantitative analysis, and bibliometric analysis. First, a qualitative thematic analysis was applied to organize the findings according to the specific objectives of the review. This categorization was based on a detailed reading of the full texts and the variables extracted, generating categories such as digital literacy, technologies addressed, instruments applied, theories used, influencing factors, barriers, and strategies.

The thematic analysis was developed using a mixed coding approach, combining deductive codes (derived from the research objectives and the defined theoretical categories) with inductive codes that emerged during the review of the full texts. The coding and organization of the data were carried out in Microsoft Excel 2021, which allowed the categories to be structured systematically, facilitating their analysis and sub-analysis. Two researchers carried out the process independently and compared the coding matrices to determine the degree of agreement, reaching an agreement rate of 82%. Discrepancies were resolved by consensus, ensuring consistency in the interpretation of the data and reinforcing the robustness of the results obtained.

Finally, a bibliometric analysis was performed using VOSviewer software version 1.6.20. To do this, the set of articles was exported from Zotero in RIS format and processed in VOSviewer, selecting the option of term co-occurrence from the study abstracts. This procedure made it possible to generate a visual map of semantic relationships between main concepts, identify thematic groupings (clusters), and explore the conceptual structure of the reviewed literature. The bibliometric analysis complemented the understanding of the connections between the different dimensions addressed by the analyzed studies.

The records identified in each database were exported in RIS format for compatibility with Zotero software. Once imported, a metadata normalization process (authors, title, year, and DOI) was performed, and duplicate records were removed using Zotero's duplicate detection feature, which was then verified manually to avoid the erroneous exclusion of relevant studies. After cleaning, a single RIS file was consolidated with the 109 articles included, which was processed in VOSviewer for bibliometric analysis. The data were retrieved between 31 January and 20 February 2025, ensuring that the set of records was consistent in terms of time and methodology.

Although the bibliometric analysis is presented within the results, its inclusion was strictly complementary to the systematic review developed under the PRISMA protocol. Its purpose was to identify publication patterns, authors, and thematic clusters that would enrich the interpretation of the findings obtained in the qualitative and quantitative synthesis. Thus, the methodological and analytical core of the study remains the systematic

review, with bibliometrics used only as an additional resource to provide a broader view of the scientific landscape.

3. Results

To prepare the results, main thematic categories related to the factors, strategies, limitations, barriers, and challenges for digital literacy in agriculture were identified, differentiated by geographical region (Europe, Asia, Latin America, and Africa). In each subsection of the results, the emerging categories and subcategories are presented, accompanied by examples and specific references that show how each topic contributes to answering the research question and meeting the objectives set. This ensures traceability between the original data, the thematic analysis, and the conclusions drawn.

3.1. Bibliometric Analysis of Scientific Output

3.1.1. Scientific Output by Country with Two or More Articles

The analysis shows that the country with the highest number of publications is China with 13 articles. Other countries with significant contributions are Ghana (6), Indonesia (5), Bangladesh (4), Thailand (4), India (4), Vietnam (3), Malaysia (2), Bolivia (2), Nigeria (2), Nigeria (Ebonyi State) (2), United Kingdom (2), and Tanzania (2). This concentration may reflect regional research priorities or greater availability of resources, as shown in Figure 3.

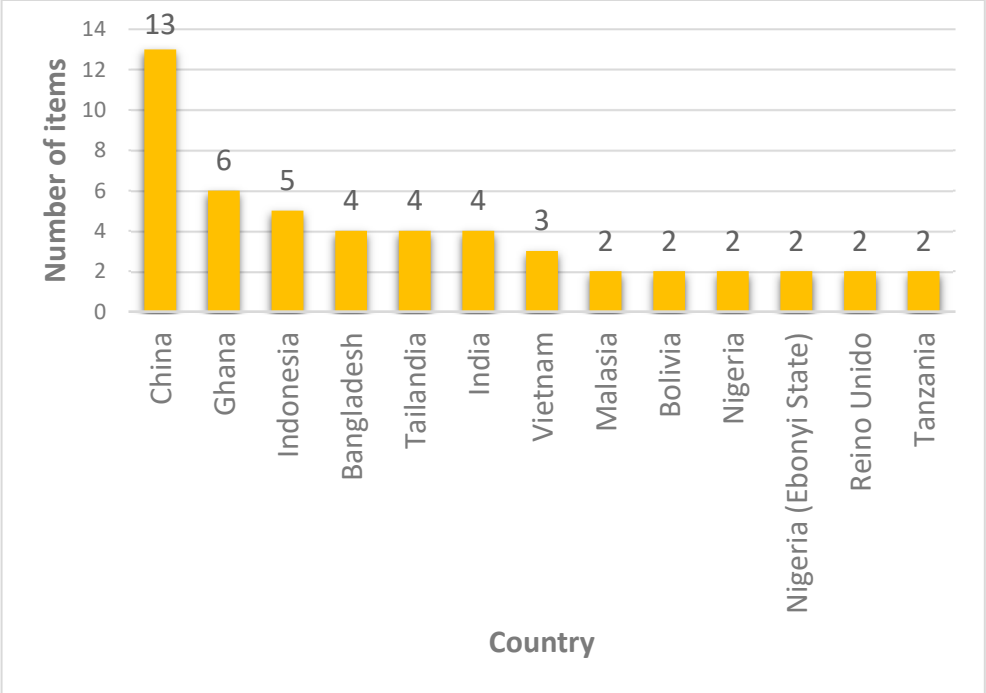


Figure 3. Scientific output with two or more articles.

3.1.2. Thematic Categories of Articles

Figure 4 shows the thematic categories identified in the articles reviewed, which reveal a diversity of approaches. The most frequent category is Decision-making and farmer behavior, with 30 publications, followed by Irrigation technologies and sustainability (20), Technology adoption in agriculture (20), Impact of technology on agricultural productivity (15), Use of information and communication technologies (ICT) in agriculture (13), and Education and training in precision agriculture (11). This reflects the interdisciplinary nature of the topic studied.

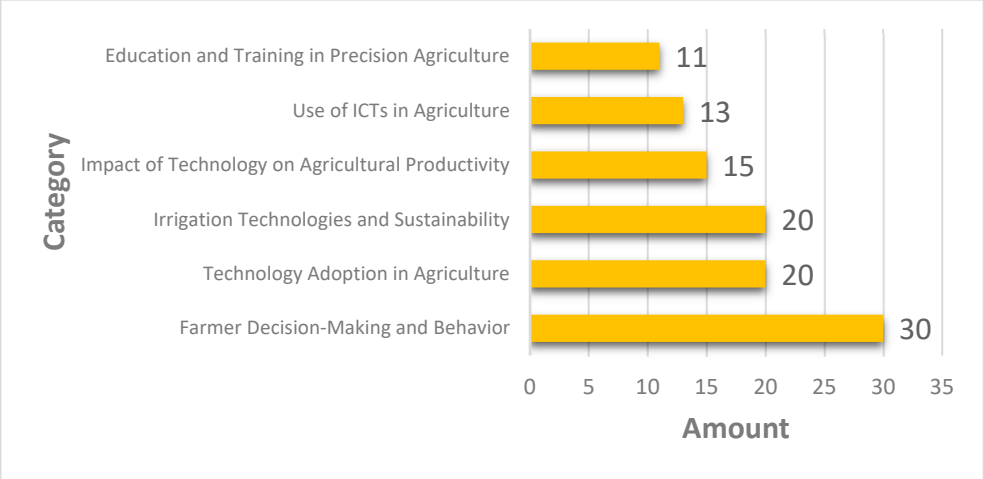


Figure 4. Number of articles by subject category.

3.1.3. Types of Documents Reviewed

Most of the documents reviewed are articles from scientific journals, with articles being the predominant type with 102 records. Conference papers are also included with 7 records, along with other formats, which shows different channels of academic dissemination, presented graphically in Figure 5.

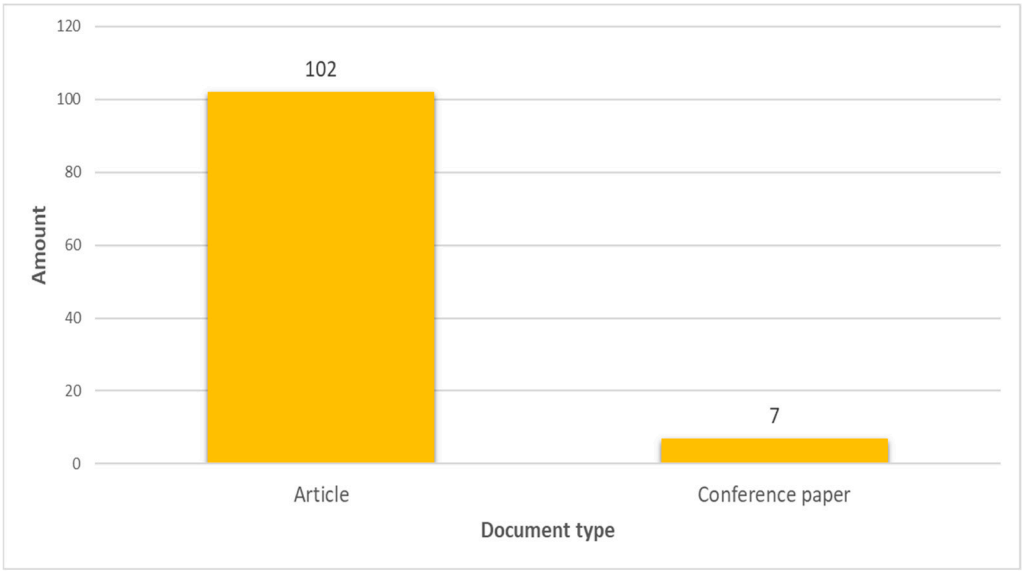


Figure 5. Type of documents reviewed.

3.1.4. Scientific Production by Year

The annual evolution of scientific production shows a growing trend in recent years, as shown in Figure 6. The year with the highest number of publications was 2024 with [26] articles, reflecting a growing academic interest in the analyzed topic of digital literacy and technology adoption in agriculture.

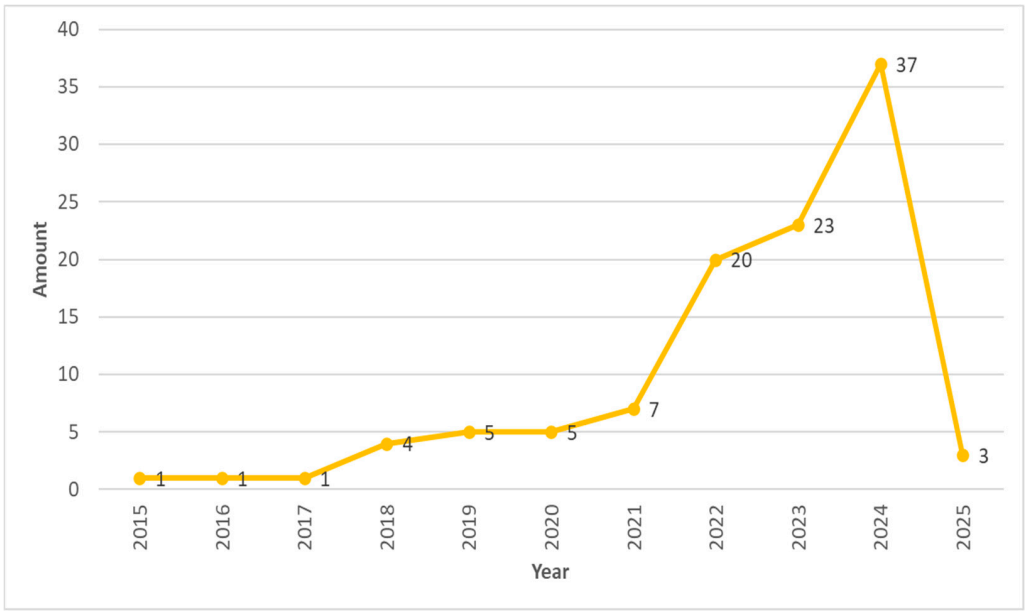


Figure 6. Scientific output by year.

3.1.5. Most Productive Authors

Based on the 'Author' column, as shown in Figure 7, the researcher with the highest number of publications is Liu, with a total of 5 articles. Other authors who also stand out in the scientific output analyzed are Addison (3), Sujianto (2), Martinez (2), Sun (2), Addai (1), Nakano (1), Mgendi (1), Mardiharini (1), and Baul (1). This analysis allows us to identify the main researchers who are leading the generation of knowledge in the field reviewed.

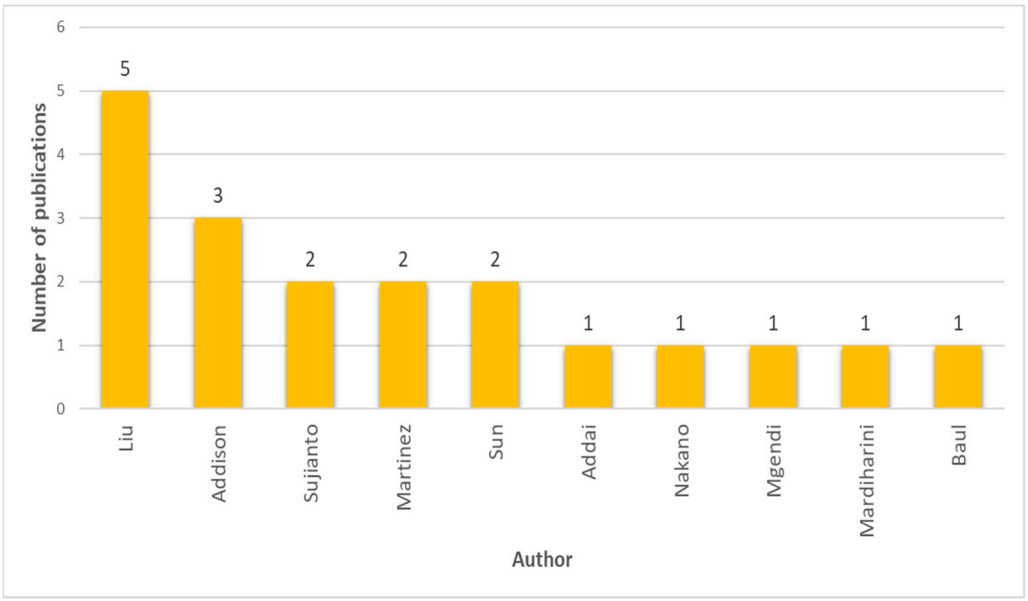


Figure 7. Number of publications by the most productive authors.

3.1.6. Publishers with the Most Articles Published

The publisher with the highest number of articles published is Multidisciplinary Digital Publishing Institute (MDPI), with a total of 15 articles. Other publishers with a significant presence include Elsevier Ltd. (12), Heliyon (7), IEEE (5), BioMed Central Ltd. (4), Journal of Innovation and Knowledge (3), De Gruyter Open Ltd. (3), Institute of Physics (3), Smart Agricultural Technology (3), and Agricultural Extension Society of Nigeria (2).

These scientific publications represent the main means of dissemination used in the studies reviewed, as shown in Figure 8.

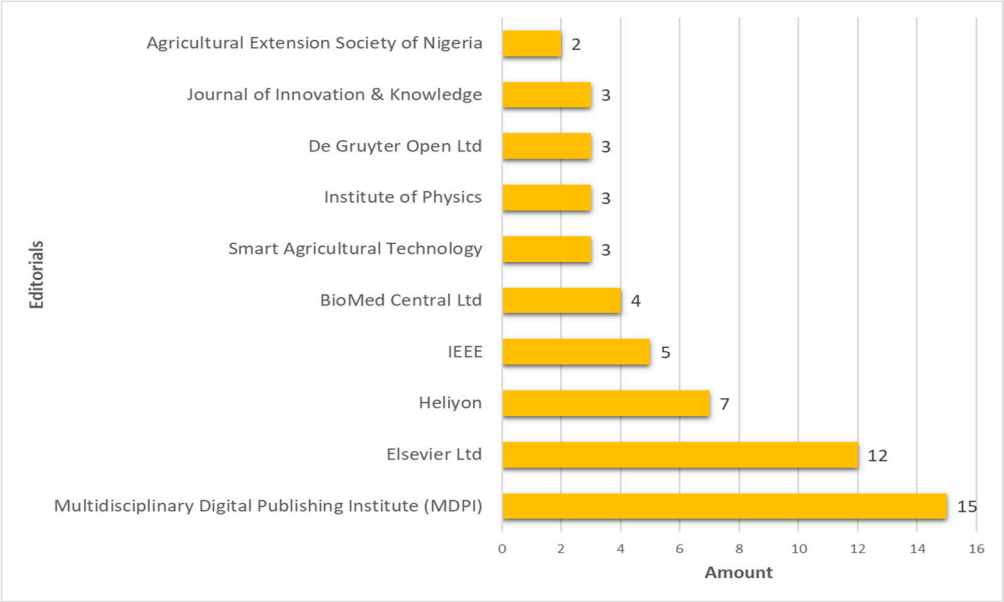


Figure 8. Publishers with the most articles published.

3.1.7. VosViewer Analysis

As part of the bibliometric analysis, a co-occurrence map of terms was constructed using VOSviewer software version 1.6.20, based on the abstracts of the 109 studies included. The objective was to identify the most frequent terms and their thematic relationship, allowing the visualization of conceptual clusters within the field of study on digital literacy and the adoption of agricultural technologies.

The resulting diagram presented in Figure 9 reveals the existence of three main clusters differentiated by color:

- Red cluster: Focused on topics related to knowledge, research, gaps, and training. Concepts such as research, training, knowledge, gap, and application are grouped in this category, indicating an academic and training approach to digital literacy and the training needs of farmers.
- Green cluster: Associated with topics related to technology adoption, agricultural outcomes, and governance. Terms such as technology adoption, government, rice, income, China, and evidence stand out, reflecting research focused on the effects of agricultural technology adoption in specific contexts, especially related to rice production.
- Blue cluster: Represents terms related to the global and climate context, such as climate change, country, importance, and smallholder farmer. This cluster connects the topic with broader structural challenges, such as sustainability and rural vulnerability.

The density of connections between terms indicates high frequencies of co-occurrence, reflecting a strong interrelationship between digital literacy, training, innovation, and agricultural outcomes. Furthermore, the centrality of terms such as training, technology adoption, and research suggests that these concepts function as semantic bridges between clusters, confirming their relevant role in scientific discourse on the topic.

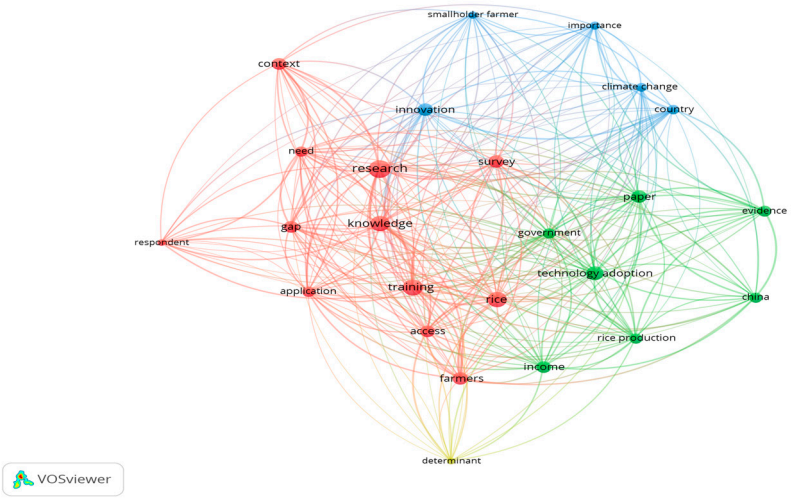


Figure 9. Map of term co-occurrence in selected articles in the RSL.

3.2. Response to Research Objectives

3.2.1. OBJ01: Describe the Main Topics, Tools, or Technologies Addressed in Digital Literacy for Farmers

Digital literacy in agriculture has focused on a wide range of topics and tools, such as the Internet of Things (IoT), precision agriculture, and the use of sensors and drones, that seek to facilitate the adoption of emerging technologies by farmers [27–29]. Training efforts have focused particularly on the use of ICT for tasks, such as irrigation management, crop monitoring, automation of agricultural processes, improving efficiency in the use of inputs, agronomic decision-making, and access to climate and market information [14,30,31]. These training courses have contributed to strengthening essential digital skills and improving the uptake of technological tools in rural contexts, although their adoption still faces infrastructure and technical training barriers.

One of the priority issues has been the use of smartphones and agricultural applications, which allow farmers to access real-time climate data, market prices, and agricultural practices [32,33]. The adoption of smartphones, analyzed through regression models that allow the understanding of factors such as age, attitude to risk, and farm size, influences the timing of adoption of these technologies [34,35]. Training in this area has proven particularly relevant for improving productivity and reducing dependence on intermediaries for access to information [15,26,36,37]. As a result, digital literacy promotes earlier and more efficient use of digital tools, thereby strengthening the digital transformation process in rural areas [37–39].

In terms of digital platforms and systems, the development of the Online Farm Trials (OFT) system stands out. This Australian platform provides structured access to agricultural data using FAIR (Findable, Accessible, Interoperable, Reusable) principles. This system has facilitated digital literacy by offering farmers a user-friendly interface to consult field trial results, compare them, and apply them to their own agricultural practices [39].

3.2.2. OBJ02: Identify the Instruments and Techniques Used to Measure the Impact of Digital Literacy on the Adoption of Agricultural Technology

Various studies have used a wide range of instruments, as well as data collection and analysis techniques, to measure the impact of digital literacy on the adoption of agricultural technology. These tools seek to capture both the digital skills and technological practices effectively implemented by farmers, as well as the associated socioeconomic variables.

One of the most common instruments is the structured survey, administered online or in person, as evidenced in studies by the authors of [13,18,30,33,35,40–51], where a

questionnaire was administered to 200 German farmers to assess the adoption of smart agricultural technologies, with questions on age, income, ICT use, and types of technology adopted [26,51–67]. These data were analyzed using econometric models, such as the Tobit regression model, to establish significant relationships between variables [13,15,39,40,42–44,46–49,58,63,68–76].

In the South African context [37], combined structured interviews with practical tests on mobile phone use, which allowed them to identify different levels of digital literacy based on everyday use of devices and applications [16,18,26,28,44,47,48,77–83]. In addition, they used checklists to observe skills such as messaging, browser use, and digital agricultural information management.

In other studies, such as that conducted by the authors of [70,84], household surveys were conducted in rural communities in China, supplemented with data from agricultural social networks. This approach made it possible to capture the impact of neighborhood networks and the demonstration effect on the adoption of digital technology. The surveys included Likert scales to measure the frequency of technology use, perceived usefulness, and confidence in digital tools [18,43,46–49,59,60,63,66].

Among the studies analyzing the relationship between digital platforms and technology adoption, research conducted in Australia [15] showed that the combined use of platform usage metrics, such as OFT and interviews with users and developers, allows for real-time identification of the impact of access to structured data under FAIR principles on digital learning. This finding is relevant to our study because it reinforces the trend identified in this systematic review, according to which the availability and standardization of data favor digital literacy processes and accelerate the adoption of technologies in agricultural environments, a key aspect for technological and economic sustainability in production chains, such as rice in Lambayeque.

3.2.3. OBJ03: Analyze the Models and Theoretical Approaches That Have Been Applied to Study the Adoption of Agricultural Technologies Based on Digital Literacy

The study of the adoption of agricultural technologies based on digital literacy has been approached from various theoretical models and methodological approaches that explain the factors that influence farmers' willingness, readiness, and behavior toward digital innovations.

Among the theoretical frameworks most used in the studies reviewed, the Technology Acceptance Model (TAM) [60,81,85] stands out, which has been fundamental in assessing how the perceived usefulness and perceived ease of use of a technology affect the intention to adopt it. This predominance was evident in our analysis, and it was observed that this model has been enriched with other approaches such as TRAM (Theory of Reasoned Action with Motivation) [72], which introduces attitude as a key mediating variable, and TRI (Technology Readiness Index) [81], which incorporates dimensions, such as optimism, innovation, insecurity, and discomfort, to measure individual willingness toward technology.

The review identified that several studies have applied econometric models, such as the Tobit regression model, to analyze the timing of adoption of technologies such as smartphones and smart farming systems. The findings of these studies show that variables such as age, farm size, and attitude toward risk influence adoption decisions, which is relevant for the design of differentiated digital literacy strategies [40].

Another important contribution comes from studies that integrate the FAIR approach, which not only improves the accessibility of digital agricultural data but also provides a theoretical framework for promoting transparency, reuse, and interoperability of information on platforms such as OFT [16].

The literature review identified a trend toward more holistic models that conceive agricultural digitization as a complex socio-technical phenomenon. Among these, ap-

proaches based on socio-cyber-physical systems (SCPS) stand out, which integrate human, technological, and environmental dimensions and facilitate the assessment of the impact of digital literacy on technology adoption at different levels of analysis [82,86].

From a more contextual perspective, some studies have also considered models such as the Agricultural Knowledge and Innovation System (AKIS) [86], which analyzes how agricultural knowledge is generated, transferred, and applied based on farmers' digital capabilities. This perspective allows digital literacy to be linked to the agricultural innovation ecosystem, considering the role of institutional actors, social networks, extension services, and digital platforms [63,70,87,88].

3.2.4. OBJ04: Determine the Main Factors Influencing Farmers' Digital Literacy and Its Relationship with the Adoption of Agricultural Technology

The results show that the age of the farmer is a determining factor in technology adoption; older producers are more resistant to using digital tools and require more time to acquire basic skills, which limits the incorporation of modern agricultural technologies [40,41,73,89]. Likewise, technological infrastructure is confirmed as an important factor; the availability of the internet, mobile phones, smart devices, and reliable electricity supply directly affects the development of digital skills. This availability is considerably lower in rural areas, which deepens the digital divide between farmers in different regions [37,50,65,90].

The findings confirm that technical training and prior education have a decisive influence on digital literacy levels. Farmers with higher formal education or participation in training programs have more developed digital skills. This shows that digital literacy does not depend solely on access to devices but also on the ability to understand, process, and apply technological information in agricultural practices [26,80,86,91].

The results show that, from a sociocultural perspective, the community environment and farmer networks have a significant influence on the development of digital skills. In contexts with a marked "neighborhood effect," producers learn by observing their peers and replicating successful practices [51,92]. This peer learning not only promotes technology adoption but also acts as an alternative and complementary channel for digital literacy [84,93].

The findings show that the relationship between digital literacy and technology adoption is bidirectional; greater digital literacy facilitates the incorporation of new technologies, while frequent use of digital tools strengthens farmers' learning and technological autonomy [83,94,95]. This synergistic dynamic highlights the need to invest not only in infrastructure but also in ongoing training programs and collaborative learning models [58,96–98].

3.2.5. OBJ05: Synthesize the Main Findings and Barriers Regarding the Relationship Between Digital Literacy and the Adoption of Agricultural Technologies Reported in the Scientific Literature

The results show that digital literacy and the adoption of agricultural technologies are closely linked, with neighborhood networks and technical education playing a prominent role [99–102]. In rural communities, peer influence acts as a catalyst for the incorporation of innovations, as many farmers replicate the practices of those with more experience or recognition in their environment. This neighborhood effect contributes to the informal transfer of digital knowledge and reduces the perception of risk associated with technology adoption [61,64,70].

The findings reveal that significant barriers to the full use of ICTs in agriculture remain. These include low levels of digital literacy, especially in intermediate and advanced skills [49,62,103], which limits the use of applications that require web browsing, data

interpretation, or interaction with digital platforms. This limitation is more pronounced among older farmers with lower levels of education or without access to formal digital training [13,37,67,104].

At the structural level, the results show the presence of barriers related to access, connectivity, and technological infrastructure, highlighting the poor quality of the internet in rural areas, the limited availability of smart mobile devices, and the lack of technical support [68,76,105]. These conditions reduce the effectiveness of digital literacy programs and restrict the active use of technological tools in agriculture. Likewise, the need to adapt technological solutions to the cultural and linguistic context of each community was identified in order to promote more inclusive and equitable adoption [54,77,86,106].

The findings indicate that factors such as farmer age, risk attitude, and farm size significantly influence technology adoption [56,107]. Younger farmers and those with larger land holdings were found to be more willing to invest in digital technologies, particularly when they identified tangible economic benefits. Likewise, analysis using econometric models, such as Tobit, confirms that digital literacy has a direct effect on both the timing and intensity of the adoption of these technologies [40,108,109].

3.2.6. OBJ06: Examine the Strategies Implemented to Improve Farmers' Digital Literacy and Their Impact on the Adoption of Emerging Technologies

Farmers' digital literacy has been addressed through various educational, technological, and community strategies aimed at closing the digital divide in rural areas and promoting the adoption of emerging technologies in agriculture [30,66,74,75]. One of the most common strategies has been to promote the use of smart mobile devices and the internet, which has allowed farmers to access climate information, market prices, technical recommendations, and agricultural applications. In the Chinese context, for example, it was observed how familiarity with these digital tools facilitated the adoption of innovative practices through social learning and the neighborhood effect [48,70,79,110].

In South Africa, digital literacy initiatives focused on personalized training through interviews and practical activities, where farmers learned to use mobile phones for basic agricultural management, such as sending messages, accessing information platforms, and contacting suppliers. This approach allowed digital skills to be built from a basic level, prioritizing functionality over technological sophistication [37,42,98].

Globally [86], the creation of digital agricultural ecosystems has been reported, including virtual training environments, access to remote extension services, and platforms for collaborative learning among farmers. These strategies have been complemented by pedagogical approaches such as co-creation of content, use of local narratives, and gamification of digital learning, which have been shown to improve motivation and retention of technical knowledge [43,111,112].

In addition, in Germany, digital literacy programs were found to have a direct impact on the intensity and timing of technology adoption, especially among young farmers or those with larger farms [46,55,113]. The incorporation of emerging technologies, such as drones, IoT sensors, and precision agriculture platforms, was faster in those groups that had previously been trained, confirming the importance of training strategies as enablers of technological change [40,80,114,115].

Overall, the strategies implemented have shown that digital literacy goes beyond mere technical learning; it also involves building confidence, ownership of tools, and the creation of knowledge-sharing networks. These actions have not only facilitated the adoption of emerging technologies but have also contributed to a structural transformation of the role of farmers in 21st-century digital agriculture [18,116–118].

3.3. Comparative Analysis by Region: Europe, Asia, Latin America, and Africa

The regional comparative analysis identified different patterns in the factors influencing digital literacy and technology adoption, as well as in the strategies implemented to strengthen these skills in agricultural contexts. In Europe, the predominant factors are related to consolidated digital infrastructure, technical training, and participation in institutional programs, while strategies focus on the use of FAIR platforms, formal training, and the integration of ICTs into agricultural policies. In Asia, technology adoption is conditioned by the generation gap, low connectivity, and the effect of community networks; strategies prioritize community training, smartphone use, and cultural adaptation of content. In Latin America, limiting factors include economic barriers, restricted access to technical support, and the need to strengthen basic digital literacy; the most common strategies include peer learning, gamification, and public outreach programs. In Africa, the main barriers stem from limited technological infrastructure, high access costs, and gender inequality, while strategies are geared toward practical training in the field, the use of community media, and the inclusion of women in ICT literacy programs.

The incorporation of this regional analysis not only allows for a comparison of the particularities of each geographical context but also identifies opportunities for the transfer of good practices. The differences found reflect the need to design digital literacy policies and programs that respond to specific socioeconomic, cultural, and technological realities, thus promoting more inclusive and sustainable technology adoption.

3.3.1. Factors Influencing Digital Literacy and Technology Adoption by Region

The information extracted from the [98] studies included was organized according to geographical region: Europe, Asia, Latin America, and Africa. Table 4 presents the main factors identified in each region, as well as the frequency with which they were cited and the key references that support them.

Table 4. Factors influencing digital literacy and technology adoption by region.

Region	Most Frequently Cited Factors	Frequency (No. of Articles)	References
Europe	– Access to the internet and smart devices. – Educational level and previous training. – Age of the farmer (young people adopt earlier). – Participation in institutional training programs. – Size of the farm.	10	[15,26,35,37,38,40,53,54,74,81]
Asia	– Generational gap in ICT use. – Low connectivity in rural areas. – Limited technological infrastructure. – Neighborhood effect and community networks. – Attitude toward risk and perception of usefulness.	17	[16,18,28,35,39,40,42,44,48,49, 52,57,58,65,82,98]

Table 4. *Cont.*

Region	Most Frequently Cited Factors	Frequency (No. of Articles)	References
Latin America	– Educational level and basic digital literacy. – Economic barriers to accessing devices. – Lack of local technical support. – Peer learning. – Influence of producer organizations.	8	[16,45,73,74,77,81,92,94]
Africa	– Poor digital infrastructure. – High costs of access to ICT. – Limited formal training. – Influence of community networks on technology adoption. – Gender gap in access to technology.	3	[16,49,81]

In comparative terms, in Europe the factors are strongly associated with digital infrastructure, formal education, and participation in institutional training programs, while in Asia, connectivity limitations and the effect of community networks stand out. In Latin America, economic constraints and the lack of technical support are more influential, although producer networks play an important role. In Africa, barriers are concentrated in infrastructure and unequal access to ICTs, with a particular emphasis on the gender gap.

3.3.2. Strategies to Improve Digital Literacy by Region

Table 5 shows the main strategies identified in the literature for each region, with their frequency and references.

Table 5. Strategies to improve digital literacy by region.

Region	Main Strategies	Frequency (Number of Articles)	References
Europe	– Institutional training programs. – FAIR platforms (e.g., OFT) with access to agricultural data. – Online courses on precision agriculture. – Collaborative learning in agricultural extension networks. – Integration of ICT in agricultural policies.	10	[26,37,38,40,54,74,81,92,93,95]
Asia	– Face-to-face community training. – Use of mobile phones for agricultural management. – Networks of leading farmers and neighborhood effect. – Cultural adaptation of content. – Training in emerging technologies (IoT, drones).	14	[18,28,39,40,42,44,49–51,53,57,58,82,98]

Table 5. *Cont.*

Region	Main Strategies	Frequency (Number of Articles)	References
Latin America	– Peer learning. – Use of local narratives in training. – Gamification of content. – Public outreach programs. – Practical field workshops.	5	[16,45,74,92,94]
Africa	– Practical field training. – Use of community radio and SMS for agricultural dissemination. – Pilot projects with close monitoring. – Integration of local leaders as trainers. – ICT literacy workshops for rural women.	1	[81]

Comparative analysis reveals that Europe leads in the use of FAIR platforms and institutionalized training, and Asia stands out for its focus on community training and mobile technologies. Latin America prioritizes culturally adapted participatory strategies, and Africa is characterized by the use of local media and inclusive approaches for women and vulnerable communities.

3.4. Limitations, Barriers, and Challenges by Region

The regional analysis not only identified the factors and strategies that influence digital literacy and technology adoption but also recognized the specific limitations, barriers, and challenges of each geographical context. Limitations refer to methodological gaps, restricted geographical coverage, or biases in the approach of the studies; barriers represent structural, technological, economic, and sociocultural obstacles that hinder the implementation of technologies. Challenges point to the priority actions required to promote inclusive and sustainable technology adoption.

Table 6 summarizes these elements for the four regions analyzed—Europe, Asia, Latin America, and Africa—allowing for comparisons to be made and recommendations tailored to each reality to be proposed.

Table 6. Constraints, barriers, and challenges by region.

Region	Constraints	Barriers	Challenges	Key References
Europe	Limited evidence in isolated rural areas; studies predominantly conducted in countries with high digital infrastructure.	Low participation of older farmers in digital programs.	Incorporate older farmers into training and technological adaptation processes.	[26,37,38,53,54]
Asia	High concentration of studies in leading countries (China, India), lower coverage in less developed areas.	Low rural connectivity, unequal access to devices, language barriers.	Develop culturally adapted, low-cost technological solutions; expand rural internet coverage.	[18,28,35,40,42,49]

Table 6. *Cont.*

Region	Constraints	Barriers	Challenges	Key References
Latin	Lack of longitudinal studies and long-term impact studies.	Lack of local technical support, economic barriers to ICT acquisition.	Implement sustained digital extension programs and foster local technical support networks.	[16,45,73,74,92]
Africa	Limited diversity of studies, concentrated in countries with international cooperation.	Limited digital infrastructure, high access costs, gender inequality in access to ICT.	Improve rural digital infrastructure, integrate inclusive programs for women and young people.	[81]

This analysis highlights that, although there are common factors and strategies across regions, the limitations and barriers respond to very specific contexts, which requires the design of differentiated digital literacy policies and programs. Likewise, the challenges identified can guide the planning of interventions that ensure more equitable, efficient, and sustainable technology adoption in each region.

4. Discussion

The review of the 109 articles analyzed identified consistent patterns and critical gaps in the factors influencing digital literacy, technology adoption, and digital skills development in the agricultural sector. The findings reveal not only an interest in digital transformation in the agricultural sector, which has grown significantly among the scientific community but also a series of tensions, gaps, and structural challenges that deserve sustained attention [70,86]. However, this interest has not necessarily translated into equitable or sustainable results in practice.

One of the most notable aspects is the persistent asymmetry between public policies and actual technology adoption practices in agricultural settings [37,40,70]. Despite the design and implementation of institutional training programs aimed at facilitating access to agricultural technologies, studies show that significant gaps persist, particularly in rural areas and vulnerable populations. This reality is exacerbated by factors such as limited connectivity, digital infrastructure, low technical training, and the cultural irrelevance of many technological proposals.

Many studies indicate that digital literacy goes beyond the instrumental use of tools; it involves a critical understanding of technology, which enables farmers to interpret, adapt, and appropriate technologies as a means of cultural, cognitive, and social mediation, depending on their contexts [37,86]. For their part, studies on precision agriculture agree that cultural and social resistance represents a more complex barrier than economic factors [40,70]. Traditional practices and the intergenerational transmission of knowledge tend to prioritize locally proven methods, reducing the willingness to experiment with new tools. Low digital literacy limits the ability to interact with platforms and devices, while mistrust of technological innovations delays the acceptance of external solutions, which are perceived as risky or alien to the context. This disconnect suggests the need for contextualized policies that incorporate the socio-territorial particularities of agriculture, especially in rural areas and indigenous communities. From a theoretical perspective, these results are in line with the social construction of technology (SCT) perspective, which argues that technology adoption is conditioned not only by its functionality but also by the interaction between users, cultural values, and social structures [26].

A point of convergence between both sectors is the importance of human and social factors in technology implementation. Evidence shows that innovation does not depend exclusively on infrastructure or technological design but on the interaction between individuals, communities, and public policies [16,86]. In this sense, technology must be understood as a social construction, and not as an end in itself.

On the other hand, a recurring gap in the articles reviewed is the lack of longitudinal studies that measure the sustained impacts of digital literacy on agricultural productivity, equity, or community resilience [37,40]. Likewise, few studies address the socio-emotional, ethical, and ecological dimensions of digital transformation in an integrated manner, opening up future lines of research around technological equity, sustainability, and digital justice [86].

The results of this review, which show the combined influence of social, educational, and technological factors on the adoption of innovations, demonstrate that digital literacy, technology adoption, and the strengthening of digital skills require intersectoral, interdisciplinary, and people-centered approaches. Technology can be a lever for transformation but only when it is integrated into conscious, participatory, and culturally rooted social processes [16,70].

In addition, other authors have written on various topics related to this research topic, regarding the impact of technology on agricultural productivity not only in rice cultivation but also in corn and cassava, as well as safe practices in the use of pesticides, associated with health problems and environmental pollution [71,119]. With regard to decision-making and agricultural behavior, the positive perception of organic farmers was analyzed, who perceive that access to agricultural information via the internet increases the adoption of climate-resilient varieties by 8% [37]. WhatsApp is the most widely used tool for immediate communication [58]. They also consider that the main problems are weeds, pests, and lack of technical knowledge [47]. Given the above, it is recommended to strengthen public extension services so that adaptation to climate change, which depends on land size, education, use of improved varieties, and technical assistance, is viable [44,47,120–122].

The comparative analysis by region shows that the influence of cultural, cognitive, social, human, and economic factors on digital literacy and technology adoption presents marked contextual differences, which conditions the effectiveness of the strategies implemented.

In Europe, cultural factors show a high level of acceptance of technological innovation, although some resistance persists in rural communities with aging populations [40]. From a cognitive perspective, high levels of digital literacy facilitate the use of complex tools such as FAIR platforms, precision agriculture systems, and real-time data analysis [16]. Formal agricultural extension networks are a key social component that promotes knowledge transfer [46]. On a human level, the generation gap remains a determining factor, as young farmers have higher rates of technology adoption. Economically, consolidated infrastructure and access to finance provide an enabling environment for digitization. Consistent with these factors, prevailing strategies include institutional training programs, online courses, and the use of FAIR platforms for the dissemination of agricultural information [16,28].

In Asia, cultural factors are conditioned by linguistic and cultural diversity, which requires adapting training content to local dialects and contexts [28]. Cognitively, there is great heterogeneity in digital skills, with significant gaps between urban and rural areas [48]. The social component is characterized by a strong neighborhood effect, where technology adoption is driven by the influence of community leaders and pioneer farmers [70]. At the human level, age and gender differences persist in access to and use of ICTs, while at the economic level, inequality in device availability and connectivity remains a critical obstacle [27]. In response, the most effective strategies include face-to-face community

training, the use of mobile phones as the primary tool, and the mobilization of agricultural leaders for technology dissemination [13,29].

In Latin America, cultural factors favor contextualized learning methodologies that incorporate local narratives and community knowledge [44]. From a cognitive standpoint, digital skills are limited, especially in rural communities with low levels of schooling [13]. Socially, producer networks and peer learning are essential channels for the transfer of technological knowledge [47]. Human factors include low average educational levels in rural areas, while economic constraints and dependence on subsidies limit the capacity to invest in digital technologies [39]. In this context, the most common strategies have been to promote peer learning, use gamification to improve motivation, and implement public agricultural extension programs [44,47].

In Africa, cultural factors are marked by a strong influence of local traditions and significant gender inequalities in access to technology [50]. Cognitively, digital literacy is in its infancy, limiting the use of more advanced technologies. Socially, community networks rely on local media, such as community radio and SMS messaging services, to disseminate agricultural information [31]. Human factors include low participation of women and young people in training programs, and economic factors are characterized by very limited access to digital infrastructure and financial resources [14]. The strategies implemented have prioritized practical training in the field, the use of community radio, and the development of inclusive programs for women and vulnerable communities [14,31].

This comparative analysis confirms that technology adoption in the agricultural sector does not respond exclusively to technical variables, but is strongly mediated by cultural, cognitive, social, human, and economic factors specific to each region. A detailed understanding of these differences is an essential basis for designing digital literacy strategies tailored to particular contexts, thereby promoting more inclusive, sustainable, and culturally relevant digital transformation processes.

From a practical perspective, the findings suggest that digital literacy programs should prioritize participatory methodologies, fostering collaborative learning and trust-building in digital environments. Public policies should focus on expanding rural connectivity, establishing incentives for the adoption of technological solutions, and promoting regulatory frameworks that ensure data interoperability and information privacy. For agricultural technology providers, the study offers evidence on the importance of developing tools with intuitive interfaces, local technical support, and accessible business models, especially for small- and medium-sized producers.

In theoretical terms, this research contributes to broadening the conceptualization of digital literacy as a multidimensional construct applicable to the agricultural sector, integrating emerging variables such as digital adaptation, technological trust, and local innovation capacity. In addition, the comparative analysis of international experiences reveals that sustainable technology adoption is most effectively achieved when digital inclusion is combined with the gradual introduction of tools, facilitating appropriation and adaptation to local realities. Together, these contributions not only synthesize the available evidence but also offer a useful reference framework for researchers, policymakers, and sector actors aimed at promoting the transition to a more productive, inclusive, and resilient agriculture in the face of the challenges of climate change and market volatility [37,86].

Finally, another aspect that has been largely overlooked in the literature is the ethical and ecological dimension of digital transformation. Only a fraction of studies considers how the adoption of technologies can reproduce gender inequalities, generational exclusion, or technological dependence. This omission represents an opportunity to expand the analysis toward approaches that integrate digital justice, environmental sustainability, and farmers' digital rights as central dimensions of the technological literacy process.

5. Conclusions

We conclude that the main themes, tools, and technologies addressed in digital literacy in agriculture have revolved around the use of sensors, IoT, drones, mobile applications, and platforms such as the OFT system. These technologies have improved agricultural decision-making, optimized resource use, and facilitated access to real-time information. However, their adoption is limited by the lack of infrastructure and the need for technical training contextualized in rural environments.

The studies reviewed show that the use of instruments, such as structured surveys, semi-structured interviews, checklists, analysis of digital platforms, as well as econometric models such as Tobit and Likert scales, has made it possible to demonstrate the relationship between digital literacy and technology adoption. The effectiveness of these tools confirms the need to assess not only technical skills but also attitudes, contexts, and social barriers that influence adoption processes.

Overall, the evidence reviewed indicates that the most widely used models, such as TAM, TRAM, TRI, AKIS, and the FAIR approach, have proven useful in explaining both the individual and systemic factors that influence technology adoption. Their application confirms that digital literacy is a multidimensional process, ranging from perceived usefulness to platform interoperability. Furthermore, the latest trends reinforce the need to adopt a socio-technical view, in which the local context and human interactions play a decisive role.

It was determined that the main factors influencing farmers' digital literacy are age, educational level, access to technological infrastructure, and the community environment. A synergistic relationship was also identified: greater digital literacy promotes technology adoption, and continued use of technology strengthens digital skills. The influence of peer learning and the neighborhood effect were also found to be fundamental in explaining the development of digital skills in rural contexts.

The articles reviewed show that the most effective strategies for promoting digital literacy in agriculture combine personalized training, easily accessible platforms, narratives adapted to the local culture, gamification elements, and collaborative learning dynamics. These approaches not only increase motivation but also reduce cultural barriers and strengthen farmers' digital autonomy. The convergence of these elements suggests that the effectiveness of programs lies in their ability to adapt to the particularities of the context and to position farmers as key actors in technological transformation processes.

Likewise, institutional strategies that integrate FAIR platforms, such as OFT, agricultural extension networks, and interactive digital ecosystems, have had a more notable impact among young farmers and those with larger production scales. These results reinforce the idea that digital literacy is not limited to access to tools but redefines the role of farmers within the 21st-century digital agricultural ecosystem, giving them a more active role in the generation, exchange, and application of knowledge.

Despite the methodological rigor applied in this systematic review, some limitations should be considered in future research. Most of the studies included come from specific geographical contexts (mainly Europe, Asia, and Latin America), which could limit the generalization of the findings to other regions with different agricultural dynamics. Furthermore, although important factors for digital literacy and technology adoption were identified, not all articles use comparable theoretical models (such as TAM, UTAUT, or TRI), making it difficult to establish universal patterns or quantifiable trends. Many studies analyze pilot cases or short-term interventions, so the long-term impacts on agricultural sustainability are still largely unexplored.

In terms of future research, it is recommended to develop longitudinal studies to assess how digital skills evolve in the agricultural population over time. Further research is also needed on the role of rural women and youth in technology adoption, as their participation

may be crucial to closing the digital divide. Finally, it is crucial to promote the creation and validation of standardized instruments to measure the impact of digital literacy on productivity, environmental sustainability, and climate resilience in the agricultural sector.

Author Contributions: Conceptualization, M.A. and H.M.; methodology, W.N.; software, H.M.; validation, M.A., H.M. and C.L.; formal analysis, C.L.; investigation, W.N.; re-sources, M.A.; data curation, W.N.; writing—original draft preparation, H.M.; writing—review and editing, M.A.; visualization, C.L.; supervision, M.A.; project administration, W.N.; funding acquisition, H.M. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported the University of Santo Toribio de Mogrovejo—020-2024-USAT-RTDO.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Nagesh, O.S.; Budaraju, R.R.; Kulkarni, S.S.; Vinay, M.; Ajibade, S.-S.M.; Chopra, M.; Jawarneh, M.; Kaliyaperumal, K. Boosting enabled efficient machine learning technique for accurate prediction of crop yield towards precision agriculture. *Discov. Sustain.* **2024**, *5*, 78. [CrossRef]
2. Ou, J.; Wu, Z.; Yan, Q.; Feng, X.; Zhao, Z. Improving soil organic carbon mapping in farmlands using machine learning models and complex cropping system information. *Environ. Sci. Eur.* **2024**, *36*, 80. [CrossRef]
3. Cheng, C.; Gao, Q.; Ju, K.; Ma, Y. How digital skills affect farmers' agricultural entrepreneurship? An explanation from factor availability. *J. Innov. Knowl.* **2024**, *9*, 100477. [CrossRef]
4. Rajalakshmi, R.; Faizal, S.; Sivasankaran, S.; Geetha, R. RiceSeedNet: Rice seed variety identification using deep neural network. *J. Agric. Food Res.* **2024**, *16*, 101062. [CrossRef]
5. Song, Y.; Dong, M.; Chen, F.; Hu, Y.; Zhu, Y.; Gu, J.; Chen, P.; Xie, Y.; Yuan, C.; Qiao, Z.; et al. Effects of Nitrogen Fertilizer Reduction Combined with Foliar Fertilizer Application on the Physiological Characteristics and Yield of High-Quality Japonica Rice. *Int. J. Plant Prod.* **2024**, *18*, 239–254. [CrossRef]
6. Wang, W.; Huang, Z.; Fu, Z.; Jia, L.; Li, Q.; Song, J. Impact of digital technology adoption on technological innovation in grain production. *J. Innov. Knowl.* **2024**, *9*, 100520. [CrossRef]
7. Ashane, M.F.; Senanayake, I.P. Developing a two-decadal time-record of rice field maps using Landsat-derived multi-index image collections with a random forest classifier: A Google Earth Engine based approach. *Inf. Process. Agric.* **2024**, *11*, 260–275. [CrossRef]
8. SaberiKamarposhti, M.; Ng, K.-W.; Yadollahi, M.; Kamyab, H.; Cheng, J.; Khorami, M. Cultivating a sustainable future in the artificial intelligence era: A comprehensive assessment of greenhouse gas emissions and removals in agriculture. *Environ. Res.* **2024**, *250*, 118528. [CrossRef]
9. Kumar, M.; Sethi, I. Computer Vision-Based Automated Detection and Severity Grading of Rice Spot Disease for Precision Management. In Proceedings of the 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 14–16 March 2024.
10. Munaganuri, R.K.; Rao, Y.N. PAMICRM: Improving Precision Agriculture Through Multimodal Image Analysis for Crop Water Requirement Estimation Using Multidomain Remote Sensing Data Samples. *IEEE Access* **2024**, *12*, 52815–52836. [CrossRef]
11. Suryavanshi, A.; Kukreja, V.; Dogra, A.; Bordoloi, D.; Joshi, K. A CNN and Random Forest Fusion with Optimized Convolutional Layers for Accurate Disease Identification in Rice Using Machine Learning. In Proceedings of the 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 14–16 March 2024.
12. Husin, N.A.; Sivajiganason, V.A.L.; Kamaruzzaman, N.N.; Mazlan, N.; Sitanggang, I.S. iRICE Decision Support System: Time-Series Forecasting Model for the Risk Management System. *J. Adv. Res. Appl. Sci. Eng. Technol.* **2024**, *33*, 160–173. [CrossRef]
13. Addison, M.; Bonuedi, I.; Arhin, A.A.; Wadei, B.; Owusu-Addo, E.; Fredua Antoh, E.; Mensah-Odum, N. Exploring the impact of agricultural digitalization on smallholder farmers' livelihoods in Ghana. *Heliyon* **2024**, *10*, e27541. [CrossRef]
14. Addai, K.N.; Temoso, O.; Ng'ombe, J.N. Heterogeneous Effects of Agricultural Technology Adoption on Smallholder Household Welfare in Ghana. *J. Agric. Appl. Econ.* **2023**, *55*, 283–303. [CrossRef]
15. Chowdhury, A.; Kabir, K.H.; McQuire, M.; Bureau, D.P. The dynamics of digital technology adoption in rainbow trout aquaculture: Exploring multi-stakeholder perceptions in Ontario using Q methodology and the theory of planned behaviour. *Aquaculture* **2025**, *594*, 741460. [CrossRef]
16. Ollerenshaw, A.; Robinson, N.; Chadha, A.; Channon, J. A smart agriculture information system delivering research data for adoption by the Australian grains industry. *Smart Agric. Technol.* **2024**, *9*, 100610. [CrossRef]

17. Elango, E.; Hanees, A.; Shanmuganathan, B.; Kareem Basha, M.I. Precision Agriculture: A Novel Approach on AI-Driven Farming. In *Intelligent Robots and Drones for Precision Agriculture*; Springer: Cham, Switzerland, 2024; pp. 119–137. [CrossRef]
18. Matthew, J.; Jamali, M.H.; Kaly Sitthan, V.; Tagang, R.R.; Ibrahim, M.H. Farmers' Perception Towards Agroforestry Practices in Siburan: Perception of Agroforestry in Siburan. *Borneo J. Resour. Sci. Technol.* **2024**, *14*, 210–216. [CrossRef]
19. Rajasekhar, V.; Arulselvi, G.; Babu, K.S. Design an optimization based ensemble machine learning framework for detecting rice leaf diseases. *Multimed. Tools Appl.* **2024**, *83*, 84401–84424. [CrossRef]
20. Sangaiah, A.K.; Yu, F.; Lin, Y.; Shen, W.; Sharma, A. UAV T-YOLO-Rice: An Enhanced Tiny Yolo Networks for Rice Leaves Diseases Detection in Paddy Agronomy. *IEEE Trans. Netw. Sci. Eng.* **2024**, *11*, 5201–5216. [CrossRef]
21. Parveen, S.; Savita; Ganguly, S. AI for Agro-Business in the Identification of Rice Diseases. In Proceedings of the 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), Greater Noida, India, 9–10 February 2024; pp. 976–982.
22. Sagar, L.; Maitra, S.; Singh, S.; Sairam, M. Advanced strategies for optimization of primary nutrients requirement in rice—A review. *Plant Sci. Today* **2024**, *11*, 353–365. [CrossRef]
23. Kusharki, M.B.; Muhammad-Bello, B.L. AIoT-Enabled Precision Agriculture for Sustainable Crop Disease Management: Advancing SDGs Through Graph Attention Neural Networks. In *Artificial Intelligence of Things for Achieving Sustainable Development Goals*; Lecture Notes on Data Engineering and Communications Technologies; Springer: Cham, Switzerland, 2024; Volume 192, pp. 143–160. [CrossRef]
24. Zhang, K.; Liang, X.; Zhang, Y.; Liu, X.; Cao, Q.; Zhu, Y.; Cao, W.; Chen, D.; Tian, Y. Unveiling the environmental and socioeconomic benefits of precision nitrogen management for paddy fields in subtropical China. *Eur. J. Agron.* **2023**, *142*, 126663. [CrossRef]
25. PRISMA Statement. PRISMA 2020 Statement. Available online: https://www.prisma-statement.org/prisma-2020 (accessed on 3 February 2025).
26. Heitkämper, K.; Reissig, L.; Bravin, E.; Glück, S.; Mann, S. Digital technology adoption for plant protection: Assembling the environmental, labour, economic and social pieces of the puzzle. *Smart Agric. Technol.* **2023**, *4*, 100148. [CrossRef]
27. Kieti, J.; Waema, T.M.; Baumüller, H.; Ndemo, E.B.; Omwansa, T.K. What really impedes the scaling out of digital services for agriculture? A Kenyan users' perspective. *Smart Agric. Technol.* **2022**, *2*, 100034. [CrossRef]
28. Nguyen, L.L.H.; Khuu, D.T.; Halibas, A.; Nguyen, T.Q. Factors That Influence the Intention of Smallholder Rice Farmers to Adopt Cleaner Production Practices: An Empirical Study of Precision Agriculture Adoption. *Eval. Rev.* **2024**, *48*, 692–735. [CrossRef] [PubMed]
29. Panyasit, K.; Singhavara, M.; Srihirun, J.; Wangsathian, S.; Nonthapot, S. A study to assess the readiness of rice farmers to use agricultural technology for production in Nong Khai Province, Thailand. *Int. J. Innov. Res. Sci. Stud.* **2024**, *7*, 607–617. [CrossRef]
30. Mou, M.A.; Paul, S.K.; Naim, J. Farmers Adaptation Strategies to Adverse Impacts of Drought on Agriculture of the Central Barind Tract of Bangladesh: An Empirical Study. *IDRiM J.* **2023**, *13*, 45–68. [CrossRef]
31. Mgendi, G.; Mao, S.; Qiao, F. Is a Training Program Sufficient to Improve the Smallholder Farmers' Productivity in Africa? Empirical Evidence from a Chinese Agricultural Technology Demonstration Center in Tanzania. *Sustainability* **2021**, *13*, 1527. [CrossRef]
32. Acheampong, L.D.; Nsiah Frimpong, B.; Adu-Appiah, A.; Asante, B.O.; Asante, M.D. Assessing the information seeking behaviour and utilization of rice farmers in the Ejisu-Juaben municipality of Ashanti Region of Ghana. *Agric. Food Secur.* **2017**, *6*, 38. [CrossRef]
33. Chhun, S.; Kumar, V.; Martin, R.J.; Srean, P.; Hadi, B.A.R. Weed management practices of smallholder rice farmers in Northwest Cambodia. *Crop Prot.* **2020**, *135*, 104793. [CrossRef]
34. Awotide, B.A.; Karimov, A.A.; Diagne, A. Agricultural technology adoption, commercialization and smallholder rice farmers' welfare in rural Nigeria. *Agric. Econ.* **2016**, *4*, 3. [CrossRef]
35. Rayhan, S.J.; Rahman, M.S.; Lyu, K. The Role of Rural Credit in Agricultural Technology Adoption: The Case of Boro Rice Farming in Bangladesh. *Agriculture* **2023**, *13*, 2179. [CrossRef]
36. Vasileiou, M.; Kyrgiakos, L.S.; Kleisiari, C.; Kleftodimos, G.; Vlontzos, G.; Belhouchette, H.; Pardalos, P.M. Transforming weed management in sustainable agriculture with artificial intelligence: A systematic literature review towards weed identification and deep learning. *Crop Prot.* **2024**, *176*, 106522. [CrossRef]
37. Alant, B.P.; Bakare, O.O. A case study of the relationship between smallholder farmers' ICT literacy levels and demographic data w.r.t. their use and adoption of ICT for weather forecasting. *Heliyon* **2021**, *7*, e06403. [CrossRef]
38. Pavithra, S.; Singh, A.; Singh, H.; Burman, R.R. Can Access to Institutional Credit Promote Adoption of Improved Technology? A Case of Biofertiliser Use Among the Indian Paddy Farmers. *Indian J. Agric. Econ.* **2024**, *79*, 739–749. [CrossRef]
39. Campenhout, B.V. The Role of Information in Agricultural Technology Adoption: Experimental Evidence from Rice Farmers in Uganda. *Econ. Dev. Cult. Change* **2021**, *69*, 1239–1272. [CrossRef]

40. Michels, M.; Musshoff, O. A tobit regression model for the timing of smartphone adoption in agriculture. *Heliyon* **2022**, *8*, e11272. [CrossRef] [PubMed]
41. Tanko, M.; Muhammed, M.A.; Ismaila, S. Reshapping agriculture technology adoption thinking: Malthus, Borlaug and Ghana's fail green revolution. *Heliyon* **2023**, *9*, e12783. [CrossRef] [PubMed]
42. Xie, C.; Zhu, Y.; Zhao, Q. How Digital Business Penetration Influences Farmers' Sense of Economic Gain: The Role of Farmers' Entrepreneurial Orientation and Market Responsiveness. *IEEE Access* **2020**, *8*, 187744–187753. [CrossRef]
43. Mao, H.; Quan, Y.; Fu, Y. Risk preferences and the low-carbon agricultural technology adoption: Evidence from rice production in China. *J. Integr. Agric.* **2023**, *22*, 2577–2590. [CrossRef]
44. Gbemavo, C.D.S.J.; Toffa, J.; Tchakpa, C.; Loko, Y.L.E.; Djedatin, G.; Ewedje, E.-E.; Orobiyi, A.; Sedah, P.; Sabot, F. Rice farmers' perceptions and response to climate variability, and determinants of adaptation strategies in the Republic of Benin. *Int. J. Clim. Change Strateg. Manag.* **2022**, *14*, 332–353. [CrossRef]
45. Liu, M.; Liu, H. Farmers' adoption of agriculture green production technologies: Perceived value or policy-driven? *Heliyon* **2024**, *10*, e23925. [CrossRef]
46. Mardiharini, M.; Jamal, E.; Rohaeni, E.S.; Indrawanto, C.; Indraningsih, K.S.; Gunawan, E.; Ramadhan, R.P.; Fahmid, I.M.; Wardana, Ï.P.; Ariningsih, E. Indonesian rice farmers' perceptions of different sources of information and their effect on farmer capability. *Open Agric.* **2023**, *8*, 20220200. [CrossRef]
47. Yaseen, M.; Shahzad, M.S.; Khan, F.U.; Luqman, M.; Saleem, U.; Nasir, S. Public Sector Advisory Services for Rice Productivity: A Case Study of Farmers' Awareness in Tehsil Shakargarh of Pakistan. *Sarhad J. Agric.* **2021**, *38*, 1–387. [CrossRef]
48. Chen, Z.-D.; Chen, F. Socio-economic factors influencing the adoption of low carbon technologies under rice production systems in China. *Carbon Balance Manag.* **2022**, *17*, 19. [CrossRef] [PubMed]
49. Susanti, E.; Safrida; Nabila, N.P.; Iskandar, E. The adoption of combine harvester and its determinant factors for sustainable rice production in Aceh Besar District, Indonesia. *IOP Conf. Ser. Earth Environ. Sci.* **2024**, *1290*, 012052. [CrossRef]
50. Ezeh, A.N.; Eze, A.V.; Eze, E.O. Extension Agents' Use of Mobile Phone Applications for Agricultural Extension Service Delivery in Ebonyi State Agricultural Development Programme, Nigeria. *J. Agric. Ext.* **2021**, *25*, 48–58. [CrossRef]
51. Ma, R.; Yang, S. The Effect of Social Network on Controlled-Release Fertilizer Use: Evidence from Rice Large-Scale Farmers in Jiangsu Province, China. *Sustainability* **2023**, *15*, 2982. [CrossRef]
52. Abdulai, S.; Zakariah, A.; Donkoh, S.A. Adoption of rice cultivation technologies and its effect on technical efficiency in Sagnarigu District of Ghana. *Cogent Food Agric.* **2018**, *4*, 1424296. [CrossRef]
53. Hossain, M.; Nayak, S.; Mohapatra, S.; Trivedi, P.; Waza, S.A. Women-led community institutions as a potential vehicle for the adoption of varieties and improved seed practices: An impact case from India. *CABI Agric. Biosci.* **2024**, *5*, 53. [CrossRef]
54. Janc, K.; Czapiewski, K.; Wójcik, M. In the starting blocks for smart agriculture: The internet as a source of knowledge in transitional agriculture. *NJAS Wagening. J. Life Sci.* **2019**, *90–91*, 100309. [CrossRef]
55. Hota, J.; Verma, V.K. Challenges to Adoption of Digital Agriculture in India. In Proceedings of the 2022 International Conference on Maintenance and Intelligent Asset Management (ICMIAM), Anand, India, 13–15 December 2022; pp. 1–6.
56. Yangchen, U.; Suebsombut, P.; Lhamo, T.; Dorji, P.; Chernbumroong, S.; Sureephong, P.; Touchard, S. Preliminary study on Smart farming literacy: A case study in Barp gewog, Punakha District, Bhutan. In Proceedings of the 2021 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunication Engineering, Cha-am, Thailand, 3–6 March 2021; pp. 340–345.
57. Sujianto; Gunawan, E.; Saptana; Syahyuti; Darwis, V.; Ashari; Syukur, M.; Ariningsih, E.; Saliem, H.P.; Mardianto, S.; et al. Farmers' perception, awareness, and constraints of organic rice farming in Indonesia. *Open Agric.* **2022**, *7*, 284–299. [CrossRef]
58. Kommey, R.E.; Fombad, M.C. Knowledge sharing technologies for rice farmers: A perspective from the Eastern Region of Ghana. *Knowl. Manag. E-Learn. Int. J.* **2024**, *16*, 355–378.
59. Ashoori, D.; Allahyari, M.S.; Bagheri, A.; Damalas, C.A. Adoption Determinants of Modern Rice Cultivars among Smallholders of Northern Iran. *Agriculture* **2019**, *9*, 232. [CrossRef]
60. Tra Vinh University; Bang, P.V.; Khanh, P.T.; Tung, D.T. The influence of cultural factors on the acceptance of alternate wetting and drying technology among rice farmers in the Vietnamese Mekong delta. *J. Sustain. Sci. Manag.* **2022**, *17*, 60–71. [CrossRef]
61. Shazwan Azizul, A.; El Pebrian, D.; Mustaffha, S.; Mariam Shamsi, S.; Zahari, M.K.; Aziera Ruslan, N. The use of drone for rice cultivation in Malaysia: Identification of factors influencing its farmers' acceptance. *J. Saudi Soc. Agric. Sci.* **2023**, *22*, 461–468. [CrossRef]
62. Goli, I.; Azadi, H.; Miceikienė, A.; Tanaskovik, V.; Stamenkovska, I.J.; Kurban, A.; Viira, A.-H. Training Needs Assessment: The Case of Female Rice Farmers in Northern Iran. *Agriculture* **2022**, *12*, 390. [CrossRef]
63. Ingram, J.; Maye, D.; Bailye, C.; Barnes, A.; Bear, C.; Bell, M.; Cutress, D.; Davies, L.; De Boon, A.; Dinnie, L.; et al. What are the priority research questions for digital agriculture? *Land Use Policy* **2022**, *114*, 105962. [CrossRef]
64. Dong, H.; Wang, H.; Han, J. Understanding Ecological Agricultural Technology Adoption in China Using an Integrated Technology Acceptance Model—Theory of Planned Behavior Model. *Front. Environ. Sci.* **2022**, *10*, 927668. [CrossRef]

65. Zikri, I.; Firda, I.; Hamid, A.H.; Susanti, E. ICT-based agricultural extension literacy and the needs for agriculture development and sustainability: A case study of rice farmer in Aceh. *IOP Conf. Ser. Earth Environ. Sci.* **2024**, *1302*, 012128. [CrossRef]
66. Meng, X.; Yang, S.; Pan, G. Innovation practices in agricultural transformation in East China: Exploring the impact and implications of the new professional farmer training model. *Heliyon* **2024**, *10*, e34671. [CrossRef]
67. Suebsombut, P.; Chernbumroong, S.; Sureephong, P.; Jaroenwanit, P.; Phuensane, P.; Sekhari, A. Comparison of Smart Agriculture Literacy of Farmers in Thailand. In Proceedings of the 2020 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON), Pattaya, Thailand, 11–14 March 2020; pp. 242–245.
68. Silva, K.N.N. Social Network to Accelerate Agricultural Technology Adoption: Evidence from Hambanthota District, Sri Lanka. *Indian J. Ext. Educ.* **2023**, *59*, 1–6. [CrossRef]
69. Cimino, A.; Coniglio, I.M.; Corvello, V.; Longo, F.; Sagawa, J.K.; Solina, V. Exploring small farmers behavioral intention to adopt digital platforms for sustainable and successful agricultural ecosystems. *Technol. Forecast. Soc. Change* **2024**, *204*, 123436. [CrossRef]
70. Mu, L.; Luo, C.; Li, Y.; Tan, Z.; Gao, S. 'They adopt, I also adopt': The neighborhood effects and irrigator farmers' conversion to adopt water-saving irrigation technology. *Agric. Water Manag.* **2024**, *305*, 109141. [CrossRef]
71. Onyeneke, C.J.; Umeh, G.N.; Onyeneke, R.U. Impact of Climate Information Services on Crop Yield in Ebonyi State, Nigeria. *Climate* **2022**, *11*, 7. [CrossRef]
72. Desmaryani, S.; Soleh, A.; Irmanelly; Wiarta, I. Integration of technology acceptance models and government support to improve digital literacy. *Heliyon* **2024**, *10*, e34086. [CrossRef] [PubMed]
73. Addison, M.; Anyomi, B.K.; Acheampong, P.P.; Wongnaa, C.A.; Amaning, T.K. Key drivers of adoption intensity of selected improved rice technologies in rural Ghana. *Sci. Afr.* **2023**, *19*, e01544. [CrossRef]
74. Oo, S.P.; Usami, K. Farmers' Perception of Good Agricultural Practices in Rice Production in Myanmar: A Case Study of Myaungmya District, Ayeyarwady Region. *Agriculture* **2020**, *10*, 249. [CrossRef]
75. Zhong, W.; Chen, Y.; Xie, L. How does internet use promote joint adoption of sustainable agricultural practices? Evidence from rice farmers in China. *Int. J. Agric. Sustain.* **2023**, *21*, 2270244. [CrossRef]
76. Sanogo, K.; Touré, I.; Arinloye, D.-D.A.A.; Dossou-Yovo, E.R.; Bayala, J. Factors affecting the adoption of climate-smart agriculture technologies in rice farming systems in Mali, West Africa. *Smart Agric. Technol.* **2023**, *5*, 100283. [CrossRef]
77. Coggins, S.; McCampbell, M.; Sharma, A.; Sharma, R.; Haefele, S.M.; Karki, E.; Hetherington, J.; Smith, J.; Brown, B. How have smallholder farmers used digital extension tools? Developer and user voices from Sub-Saharan Africa, South Asia and Southeast Asia. *Glob. Food Secur.* **2022**, *32*, 100577. [CrossRef]
78. Ali, S.; Murtaza, M.; Ahmad, W.; Bibi, N.; Khan, A.; Khan, J. Does Education and Farming Experience Affect Technical Efficiency of Rice Crop Growers? Evidence from Khyber Pakhtunkhwa, Pakistan. *Sarhad J. Agric.* **2022**, *38*, 1147–1159. [CrossRef]
79. Pham, V.B.; Diep, T.T.; Fock, K.; Nguyen, T.S. Using the Internet of Things to promote alternate wetting and drying irrigation for rice in Vietnam's Mekong Delta. *Agron. Sustain. Dev.* **2021**, *41*, 43. [CrossRef]
80. Karubanga, G.; Godfrey Agea, J.; Tatenda Rugare, J.; Mubangizi, N. Leveraging video integration for enhanced agricultural extension reforms in Uganda. *Cogent Soc. Sci.* **2024**, *10*, 2399936. [CrossRef]
81. Najjar, D.; Baruah, B. Beer, barley, livestock, milk: Who adopts agricultural innovations in rural Rajasthan? *World Dev. Perspect.* **2024**, *36*, 100643. [CrossRef] [PubMed]
82. Metta, M.; Ciliberti, S.; Obi, C.; Bartolini, F.; Klerkx, L.; Brunori, G. An integrated socio-cyber-physical system framework to assess responsible digitalisation in agriculture: A first application with Living Labs in Europe. *Agric. Syst.* **2022**, *203*, 103533. [CrossRef]
83. Chindasombatcharoen, N.; Tsolakis, N.; Kumar, M.; O'Sullivan, E. Navigating psychological barriers in agricultural innovation adoption: A multi-stakeholder perspective. *J. Clean. Prod.* **2024**, *475*, 143695. [CrossRef]
84. Liu, K.; Qi, Z.; Tan, L.; Hu, C. How Neighbors Influence Rice–Crayfish Integrated System Adoption: Evidence from 980 Farmers in the Lower and Middle Reaches of the Yangtze River. *Int. J. Environ. Res. Public Health* **2023**, *20*, 4399. [CrossRef]
85. Wu, Y.; Takács-György, K. What is stopping Agriculture 4.0?—Examples from China. In Proceedings of the 2023 IEEE 17th International Symposium on Applied Computational Intelligence and Informatics (SACI), Timisoara, Romania, 23–26 May 2023; pp. 000511–000518.
86. Jakobsen, K.; Mikalsen, M.; Lilleng, G. A literature review of smart technology domains with implications for research on smart rural communities. *Technol. Soc.* **2023**, *75*, 102397. [CrossRef]
87. Chamorro-Padial, J.; Virgili-Gomá, J.; Gil, R.; Teixidó, M.; García, R. Agriculture data sharing review. *Heliyon* **2025**, *11*, e41109. [CrossRef]
88. Kunlerd, A.; Nabumroong, B.; Jantarakomet, K.; Ruttanaprasert, R.; Burana, K. Analyzing Success Factors in Developing Mobile Applications for Farmers in Thailand Using Analytic Hierarchy Process Technique. *Indones. J. Electr. Eng. Inform. IJEEI* **2024**, *12*, 1019–1031. [CrossRef]

89. Khoy, R.; Nanseki, T.; Chomei, Y. Farmers' Perceptions of Government's Rice Export Policy: A Case in Southern Cambodia. *J. Fac. Agric. Kyushu Univ.* **2018**, *63*, 469–477. [CrossRef]
90. Addison, M.; Ohene-Yankyera, K.; Acheampong, P.P.; Wongnaa, C.A. The impact of uptake of selected agricultural technologies on rice farmers' income distribution in Ghana. *Agric. Food Secur.* **2022**, *11*, 2. [CrossRef]
91. Xiao, J.; Xu, Z.; Xiao, A.; Wang, X.; Skare, M. Overcoming barriers and seizing opportunities in the innovative adoption of next-generation digital technologies. *J. Innov. Knowl.* **2024**, *9*, 100622. [CrossRef]
92. Nakano, Y.; Tsusaka, T.W.; Aida, T.; Pede, V.O. Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania. *World Dev.* **2018**, *105*, 336–351. [CrossRef]
93. Sujianto, S.; Hasibuan, A.M.; Mahendri, I.G.A.P.; Pribadi, E.R.; Pujiharti, Y.; Ardana, I.K.; Ermiati; Sudjarmoko, B.; Sukamto; Gunawan, E. Drivers of Organic Rice Adoption Among Smallholder Farmers: Implications for Sustainable Development. *Int. J. Sustain. Dev. Plan.* **2024**, *19*, 289–299. [CrossRef]
94. Baul, T.; Karlan, D.; Toyama, K.; Vasilaky, K. Improving smallholder agriculture via video-based group extension. *J. Dev. Econ.* **2024**, *169*, 103267. [CrossRef]
95. Gómez-Carmona, O.; Buján-Carballal, D.; Casado-Mansilla, D.; López-de-Ipiña, D.; Cano-Benito, J.; Cimmino, A.; Poveda-Villalón, M.; García-Castro, R.; Almela-Miralles, J.; Apostolidis, D.; et al. Mind the gap: The AURORAL ecosystem for the digital transformation of smart communities and rural areas. *Technol. Soc.* **2023**, *74*, 102304. [CrossRef]
96. Agussabti, A.; Rahmaddiansyah, R.; Hamid, A.H.; Zakaria, Z.; Munawar, A.A.; Abu Bakar, B. Farmers' perspectives on the adoption of smart farming technology to support food farming in Aceh Province, Indonesia. *Open Agric.* **2022**, *7*, 857–870. [CrossRef]
97. Dar, M.H.; Waza, S.A.; Nayak, S.; Chakravorty, R.; Zaidi, N.W.; Hossain, M. Gender focused training and knowledge enhances the adoption of climate resilient seeds. *Technol. Soc.* **2020**, *63*, 101388. [CrossRef]
98. Liu, D.; Huang, Y.; Luo, X. Farmers' technology preference and influencing factors for pesticide reduction: Evidence from Hubei Province, China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 6424–6434. [CrossRef]
99. Badiru, I.O. Impact of Extension Services and Input Consultants' Activities on Crop Yields of Fadama III Additional Financing Farmers in Nigeria. *J. Agric. Ext.* **2024**, *28*, 42–49. [CrossRef]
100. Martinez, J.M.; Labarta, R.A.; Gonzalez, C. Impacts of the joint adoption of improved varieties and chemical fertilizers on rice productivity in Bolivia: Implications for Global Food Systems. *Front. Sustain. Food Syst.* **2023**, *7*, 1194930. [CrossRef]
101. Martinez, J.M.; Labarta, R.A.; Gonzalez, C.; Lopera, D.C. Joint adoption of rice technologies among Bolivian farmers. *Agric. Resour. Econom. Rev.* **2021**, *50*, 252–272. [CrossRef]
102. Ehlers, M.-H.; Finger, R.; El Benni, N.; Gocht, A.; Sørensen, C.A.G.; Gusset, M.; Pfeifer, C.; Poppe, K.; Regan, Á.; Rose, D.C.; et al. Scenarios for European agricultural policymaking in the era of digitalisation. *Agric. Syst.* **2022**, *196*, 103318. [CrossRef]
103. Clarkson, G.; Dorward, P.; Poskitt, S.; Stern, R.D.; Nyirongo, D.; Fara, K.; Gathenya, J.M.; Staub, C.G.; Trotman, A.; Nsengiyumva, G.; et al. Stimulating small-scale farmer innovation and adaptation with Participatory Integrated Climate Services for Agriculture (PICSA): Lessons from successful implementation in Africa, Latin America, the Caribbean and South Asia. *Clim. Serv.* **2022**, *26*, 100298. [CrossRef]
104. Pandeya, S.; Gajurel, A.; Mishra, B.P.; Devkota, K.; Gyawali, B.R.; Upadhaya, S. Determinants of Climate-Smart Agriculture Adoption Among Rice Farmers: Enhancing Sustainability. *Sustainability* **2024**, *16*, 10247. [CrossRef]
105. Kamanda, P.J.; Motaung, M.V.; Okorley, E.L. Socio-demographic Characteristics of Smallholder Farmers That Influence Their Competence in Rice Post-Harvest Value Addition, Southern Region of Sierra Leone. *Univers. J. Agric. Res.* **2023**, *11*, 680–690. [CrossRef]
106. Tetteh Quarshie, P.; Abdulai, A.-R.; Duncan, E.; Bahadur Kc, K.; Roth, R.; Sneyd, A.; Fraser, E.D.G. Myth or reality? The Digitalization of Climate-Smart Agriculture (DCSA) practices in smallholding agriculture in the Bono East Region of Ghana. *Clim. Risk Manag.* **2023**, *42*, 100553. [CrossRef]
107. Baratella, V.; Pirelli, T.; Giordano, R.; Pagano, A.; Portoghese, I.; Bea, M.; López-Moya, E.; Di Fonzo, A.; Fabiani, S.; Vanino, S. Stakeholders analysis and engagement to address Water-Ecosystem-Food Nexus challenges in Mediterranean environments: A case study in Italy. *Ital. J. Agron.* **2023**, *18*, 2200. [CrossRef]
108. Begen, N.; Atasoy, H. Technological literacy and employment: An inquiry into the adoption of learning technologies. *Telecommun. Policy* **2024**, *48*, 102864. [CrossRef]
109. Liu, Y.; Razman, M.R.; Syed Zakaria, S.Z.; Ern, L.K.; Hussain, A.; Chamola, V. Utilizing ubiquitous learning to foster sustainable development in rural areas: Insights from 6G technology. *Comput. Hum. Behav.* **2024**, *161*, 108418. [CrossRef]
110. Surdianto, Y.; Sutrisna, N.; Nurawan, A.; Hamdani, K.K.; Wiratno, W.; Erythrina, E.; Sugandi, D. Study of Rice (*Oryza sativa*) Seed Breeding Based on Farmer Groups in Pangandaran Regency, West Java Province, Indonesia. *IOP Conf. Ser. Earth Environ. Sci.* **2024**, *1364*, 012020. [CrossRef]
111. Alam, M.J.; Sarma, P.K.; Begum, I.A.; Connor, J.; Crase, L.; Sayem, S.M.; McKenzie, A.M. Agricultural extension service, technology adoption, and production risk nexus: Evidence from Bangladesh. *Heliyon* **2024**, *10*, e34226. [CrossRef]

112. Sekiya, N.; Tomitaka, M.; Oizumi, N.; Assenga, A.N.; Jacob, M.K. Farmer-to-Farmer Extension Facilitated by Agricultural Training Institutions: A Case of NERICA Dissemination in Tanzania. *Plant Prod. Sci.* **2015**, *18*, 398–406. [CrossRef]
113. Asiedu-Ayeh, L.O.; Zheng, X.; Agbodah, K.; Dogbe, B.S.; Darko, A.P. Promoting the Adoption of Agricultural Green Production Technologies for Sustainable Farming: A Multi-Attribute Decision Analysis. *Sustainability* **2022**, *14*, 9977. [CrossRef]
114. Kakumanu, K.R.; Kotapati, G.R.; Nagothu, U.S.; Kuppanan, P.; Kallam, S.R. Adaptation to climate change and variability: A case of direct seeded rice in Andhra Pradesh, India. *J. Water Clim. Change* **2019**, *10*, 419–430. [CrossRef]
115. Kuang, F.; Li, J.; Jin, J.; Qiu, X. Do Green Production Technologies Improve Household Income? Evidence from Rice Farmers in China. *Land* **2023**, *12*, 1848. [CrossRef]
116. Tun Oo, A.; Cho, A.; Yan Naing, S.; Marin, G. Determining factors and barriers to the uptake of climate change adaptation strategies of agriculture and aquaculture farm households in Myanmar. *Int. J. Clim. Change Strateg. Manag.* **2024**, *16*, 253–272. [CrossRef]
117. Sun, J.; Zhan, J.; Chen, Z. Agricultural Insurance and Selection of Soil Testing and Formula Fertilization Technology—An Empirical Study Based on the Main Rice-Producing Areas in China. *Sustainability* **2024**, *16*, 9222. [CrossRef]
118. Liu, B.; Li, N.; Liao, C. Effects of Social Capital on the Adoption of Green Production Technologies by Rice Farmers: Moderation Effects Based on Risk Preferences. *Sustainability* **2024**, *16*, 8879. [CrossRef]
119. Ndayambaje, B.; Amuguni, H.; Coffin-Schmitt, J.; Sibo, N.; Ntawubizi, M.; VanWormer, E. Pesticide Application Practices and Knowledge among Small-Scale Local Rice Growers and Communities in Rwanda: A Cross-Sectional Study. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4770. [CrossRef]
120. Bhardwaj, S.; Baljinder, K.S. Groundwater Depletion and Role of Direct Seeded Rice in Water Saving: A Move Towards Sustainable Agriculture of Punjab. *Econ. Aff.* **2019**, *64*, 25–33. [CrossRef]
121. Sun, X.; Lyu, J.; Ge, C. Knowledge and Farmers' Adoption of Green Production Technologies: An Empirical Study on IPM Adoption Intention in Major Indica-Rice-Producing Areas in the Anhui Province of China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 14292. [CrossRef]
122. Lakitan, B.; Hadi, B.; Herlinda, S.; Siaga, E.; Widuri, L.I.; Kartika, K.; Lindiana, L.; Yunindyawati, Y.; Meihana, M. Recognizing farmers' practices and constraints for intensifying rice production at Riparian Wetlands in Indonesia. *NJAS Wagening. J. Life Sci.* **2018**, *85*, 10–20. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.