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INVESTIGATING THE SYSTEMIC DIMENSION OF AGRICULTURAL TECHNOLOGY ADOPTION PROCESS: A MIXED-METHOD ANALYSIS OF THE ADOPTION DETERMINANTS THROUGH THE PERCEPTIONS OF ITALIAN STAKEHOLDERS

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Abstract

Digital technologies are increasingly recognised as strategic enablers for transforming agri-food systems toward sustainability, efficiency, and competitiveness. Nevertheless, despite their potential, adoption by farmers remains limited and uneven across contexts. Existing research has predominantly focused on farm-level determinants such as attitudes, perceived usefulness and benefits, economic constraints, and technological characteristics, whereas the role of systemic interactions, including stakeholder networks, advisory infrastructures, governance arrangements, and data ecosystems in shaping farmers' behaviour remains insufficiently investigated. The present dissertation addresses this knowledge gap by examining how individual and systemic factors jointly influence the adoption of digital technologies in agriculture, specifically through the lens of the Italian stakeholder landscape. The work is grounded in the assumption that technology adoption is the outcome of a dynamic interplay between individual behavioural processes and the broader configuration of the innovation ecosystem. Accordingly, the research adopts a multilevel perspective, investigating both the determinants that drive farmers' intentions to adopt digital technologies and the systemic conditions that influence and support the translation of those intentions into action over time.

To operationalise this perspective, the study adopts a sequential mixed-method design articulating three interconnected phases. First, by means of a systematic and a scoping review, this thesis clarifies the conceptual boundaries of the systemic dimension of adoption, identifying key systemic determinants and exposing their persistent underrepresentation in empirical research. The literature reveals a strong dominance of individual-level factors, limited theoretical grounding, and a fragmented treatment of governance and value-chain dynamics, highlighting the need for a structural shift in how adoption is investigated. Second, through an explorative stakeholder study in Italy, the thesis provides a contextualised understanding of digitalisation barriers and opportunities. Farmers, advisors, cooperatives, technology providers, and policymakers collectively emphasise that market and advisory fragmentation, weak cooperation mechanisms, and misalignment between technological supply and farm needs are structural constraints that cannot be overcome by training or incentives alone. At the same time, stakeholders recognise economic and environmental pressures as strong drivers for change, revealing that, despite this motivation, the innovation ecosystem, as identified by stakeholders is not yet able to effectively support widespread adoption.

Third, a nationwide survey empirically tests these insights within an extended Theory of Planned Behaviour framework, in which constructs such as Technical Support and Climate Change Perception are explicitly incorporated. Results from structural modelling provide robust evidence that intention strongly predicts both possession and actual use of digital technologies, and that Technical Support acts as a primary enabler of intention, with a magnitude comparable to core attitudinal factors. Conversely, the limited role of subjective norms reflects the weak diffusion of peer influence in a fragmented farming landscape.

Overall, this dissertation demonstrates that adoption does not scale without supportive ecosystems: coordination mechanisms, robust advisory services, coherent governance, and data integrationemerge as major bottleneck for digital agriculture.

This evidence calls for policy strategies that jointly target both domains: fostering multi-actor innovation networks and advisory infrastructures that generate trust, shared value, and learning; while designing interventions that account for the interaction between individual motivations and structural conditions. By articulating and empirically validating the systemic dimension alongside behavioural determinants, this thesis offers a more comprehensive perspective that informs efforts to strengthen and accelerate the digital transition of agriculture.

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1. Introduction

1.1. Background and motivation

The global agricultural sector is confronted with the dual challenge of increasing productivity to meet the growing demand for food, feed, and fibre, while simultaneously addressing pressing environmental concerns. In Europe, this ambition is embedded in strategic frameworks such as the Green Deal and the Farm to Fork Strategy, which call for a profound transformation of agri-food systems towards sustainability. Within this transition, technological innovation, with reference to the broader socio-technical change in practices, organisation, and value-chain coordination, has emerged as a key driver, offering solutions that can enhance productivity, optimise resource use, and strengthen resilience to climate risks.

Digital agriculture, conceived as an evolution of precision farming, encompasses the integration of sensors, remote sensing, the Internet of Things, big data analytics, and decision support systems into farming practices. These tools generate and process vast amounts of data, enabling more informed and efficient management of agricultural operations. However, despite their potential benefits, the adoption of such technologies remains uneven, hindered by structural, socio-economic, and institutional barriers.

The literature on agricultural technology adoption highlights the complexity of the process, which is shaped by multiple interacting factors including farm and farmer characteristics, perceived economic benefits, technological attributes, institutional support, and attitudinal dimensions. While many studies have addressed adoption at the farm level, recent research emphasises the importance of a broader systemic perspective (Shang et al., 2021)- one that considers the network of actors, governance structures, market dynamics, and policy frameworks that influence technology uptake. This systemic dimension encompasses interactions among stakeholders - such as farmers, cooperatives, advisors, technology providers, and policymakers - which can facilitate or hinder the diffusion of innovation (McGrath et al., 2023; Osrof et al., 2023; Sadjadi and Fernández, 2023).

In the Italian context, the digital transition in agriculture is still at an early stage. Evidence points to significant mismatches between the technological solutions offered and the actual needs of farms, with limited capacity to collect, integrate, and exploit data effectively.

Barriers such as high investment costs, lack of technical skills, inadequate advisory services, and fragmented market development further constrain adoption. At the same time, drivers such as improved economic performance, environmental benefits, regulatory requirements, and stronger stakeholder cooperation have the potential to accelerate uptake.

Recent evidence also shows that participation in structured innovation networks, such as Operational Groups promoted under the EIP-AGRI framework, is associated with improved farm economic performance (Mazzulla and Raggi, 2025). This underscores the role of governance and collective arrangements not only as drivers of adoption but also as contributors to competitiveness. In fact, in addition to the economic dimension, strengthening membership groups emerged as essential to promoting farmers' acceptance of new technologies (Castellini et al., 2025).

Despite growing academic interest, important gaps remain. There is still no convergence in the theoretical models used to explain technology adoption, and systemic factors - such as stakeholder perceptions, governance arrangements, and supply chain dynamics - are often underrepresented in empirical studies (Gemtou et al., 2024; Guerrieri et al., 2025; Osrof et al., 2023). This underrepresentation is particularly critical given that systemic factors, such as stakeholder engagement, governance arrangements, institutional coordination, and market structures, play a decisive role in shaping the conditions for successful adoption and diffusion of innovation. Current research tends to fragment these elements, addressing them only indirectly or in isolation, without providing a coherent framework for how interactions across the agricultural innovation system influence individual farmers' decisions. As a result, there is limited understanding of how policies, supply chain dynamics, and multi-actor relationships can be leveraged to create enabling environments for adoption.

This gap in the literature justifies the need for a targeted and structured review, specifically aimed at mapping how the systemic dimension has been conceptualised, operationalised, and empirically investigated in the context of agricultural technology adoption.

Thereby, particular attention was paid to the systemic dimension of adoption - defined as the network of relationships, infrastructures, governance arrangements, and institutional frameworks that shape the conditions for technology uptake (McGrath et al., 2023; Osrof et al., 2023; Sadjadi and Fernández, 2023).

In operational terms, the systemic dimension is captured by the set of actors, institutions, infrastructures, and coordination mechanisms that surround the farm and shape adoption opportunities and constraints. The stakeholder evidence is then interpreted to assess whether these systemic arrangements are sufficient to support adoption beyond isolated cases and early adopters.

Against this backdrop, the present research is motivated by the need to integrate individual and systemic dimensions in the analysis of digital technology adoption in the Italian agricultural context, addressing the process from a technology-neutral perspective and combining multiple sources of evidence.

To this end, the present study follows a sequential, mixed-methods design articulated in three interconnected phases (Figure 1).

Phase 1 – Literature review and scoping study. A systematic literature review was conducted to map the determinants of digital technology adoption and the theoretical frameworks employed in previous studies. Particular attention was devoted to systemic factors, which were further examined through a dedicated scoping review. Results from this phase confirmed the predominance of individual-level determinants (e.g., attitudes, skills, perceived usefulness) and revealed the underrepresentation of systemic drivers such as governance, institutional support, and stakeholder interactions. This dual review provided the conceptual foundations for the empirical framework.

Phase 2 – Exploratory qualitative study. Building on the literature review, interviews with Italian stakeholders (farmers, cooperatives, advisors, technology providers, and policymakers) were conducted to contextualise adoption factors and capture perceptions of barriers, drivers, and needs. The findings highlighted critical issues such as the lack of effective advisory systems, the mismatch between technological supply and farm demand, and the need for stronger cooperation mechanisms. At the same time, stakeholders recognised opportunities linked to cost reduction, environmental compliance, and improved competitiveness. These insights validated the factors identified in Phase 1 and informed the design of the subsequent survey instrument.

Phase 3 – Quantitative survey and modelling. Finally, a nationwide survey of Italian farmers tested an extended behavioural model of adoption, rooted in the Theory of Planned Behaviour (TPB) and enriched with systemic constructs emerging from the previous phases. In particular, the quantitative analysis incorporated additional variables such as Technical Support and Climate Change Perception, identified as salient drivers in both the literature and the qualitative study. Results showed that Attitude and Perceived Behavioural Control exerted the strongest influence on adoption intention, while Technical Support also emerged as a significant enabler. Intention was further confirmed as the key predictor of both possession and effective use of digital technologies, highlighting the central role of behavioural readiness in driving actual adoption.

The research question addressed by this dissertation is multi-level: it involves (i) mapping determinants and theoretical approaches in the literature, (ii) identifying ecosystem mechanisms and coordination constraints from key actors, and (iii) testing an extended behavioural model on farmers. A survey-only design would risk overlooking the contextual and institutional mechanisms through which adoption constraints materialise, while a qualitative-only design would limit generalisability and hinder the empirical testing of the extended model.

A sequential design is therefore adopted to ensure construct refinement and triangulation: the literature review informs the interview protocol and the selection of constructs; qualitative insights help interpret and contextualise quantitative results; and the survey provides confirmatory evidence on the relative weight of psychological and systemic factors. In line with Starr, (2014), this mixed-method positioning is especially appropriate when open-ended inquiry is needed to characterise complex phenomena and to complement closed-ended measurement with richer contextual understanding. This positioning aligns with methodological discussions highlighting the contribution of qualitative and mixed-methods approaches to improve interpretability and policy relevance in applied economic research (Starr, 2014).

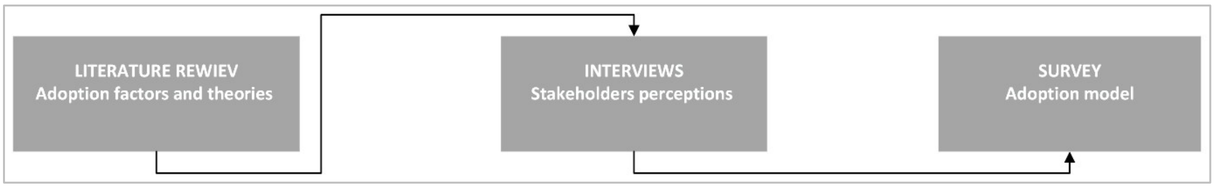


Figure 1 - Empirical framework

This sequential design ensures a strong connection between theory and empirical evidence. Each phase of the framework builds upon the previous one, enabling triangulation of results and enhancing the robustness of findings. The literature review established the state of the art and highlighted gaps, the qualitative study contextualised and deepened the understanding of systemic barriers and drivers, and the quantitative survey operationalised and tested an extended adoption model.

Ultimately, this integrated framework provides actionable insights for both policy and practice. It shows that while individual attitudes and capacities remain crucial, systemic enablers—such as advisory services, governance arrangements, and stakeholder cooperation—

play a decisive role in shaping the conditions for successful adoption. By combining multiple sources of evidence and perspectives, the study contributes to filling the knowledge gap on how individual and systemic factors interact to influence digital technology adoption in agriculture, further supporting the view that systemic factors are not only complementary but essential to the digital transition.

1.2. Objectives

The overarching aim of this research is to investigate the process of digital technology adoption in agriculture, with a particular focus on the Italian farming context. The study adopts a multi-stage, mixed-method approach to provide a comprehensive understanding of the determinants, perceptions, and behavioral mechanisms underlying adoption.

More specifically, the research pursues the following objectives:

- To identify the factors and theoretical frameworks that have been applied to explain the adoption of digital technologies in agriculture, thereby establishing the state of the art in terms of both determinants and modelling approaches.
- To capture the perceptions of Italian stakeholders regarding the barriers and drivers of technology adoption, with the aim of enriching and contextualising the factors identified in the literature.
- To assess the influence of attitudinal and systemic factors on farmers' intention to adopt digital technologies, through the empirical testing of an extended adoption model.

By achieving these objectives, the study seeks to generate actionable insights for both academic research and policy interventions aimed at fostering the digital transition in agriculture.

1.3. Novelties

This research stands out from existing literature, offering several novel contributions to the adoption of agricultural technology. First, it adopts a technology-neutral perspective, investigating the adoption process without focusing on a specific technological field or practice. This approach enables the derivation of a general framework for understanding adoption, with particular emphasis on its attitudinal and systemic dimensions.

Second, it addresses a well-recognised gap in the literature regarding the application of mixed-method designs. While most prior studies have examined adoption mainly at the farm level, this work integrates the perspectives of multiple stakeholders across the farming supply chain. Analysing their perceptions and needs provides a broader understanding of adoption dynamics and offers practical insights to guide research and policy frameworks that are more closely aligned with farmers' requirements—thus fostering trust and positive attitudes towards the digital transition.

Third, it extends the well-established Theory of Planned Behavior (TPB) by integrating specific adoption factors identified through stakeholder interviews. This theoretically informed and empirically grounded extension yields a deeper and more context-sensitive understanding of the mechanisms underpinning the adoption and diffusion of digital technologies in agriculture.

1.4. Overview

This dissertation is structured into five chapters, each contributing to a comprehensive investigation of the factors influencing the adoption of digital technologies in agriculture.

Chapter 2 presents a comprehensive review of the literature on the adoption of agricultural technology. It identifies the main factors affecting adoption and synthesises the theoretical approaches most frequently used to model this process. To address specific gaps in the existing body of knowledge, a complementary scoping review was conducted focusing on the systemic dimension of adoption, thus refining the theoretical framework and culminating in a scientific publication (Addorisio et al., 2025b). The chapter builds the state of the art by mapping both the determinants of adoption and the prevailing theoretical perspectives.

Chapter 3 reports the findings of an exploratory empirical study based on interviews with Italian stakeholders. Building on the literature review, this qualitative investigation – published as a scientific article (Addorisio et al., 2025a) captured stakeholders' perceptions of the drivers, barriers, and systemic challenges related to the digital transition in Italian agriculture. The analysis deepened the understanding of the underlying elements of the adoption process and informed the design of the subsequent quantitative phase.

Chapter 4 presents a quantitative study aimed at assessing the role of attitudinal and systemic factors in shaping farmers' intention to adopt digital technologies. Drawing on the factors identified in the previous stages, the Theory of Planned Behavior (TPB) model was extended in line with the insights from the qualitative study. The resulting adoption model was tested through a survey administered to Italian farmers. Building on the literature review and qualitative studies' insights, this chapter sheds light on the determinants of adoption intention, while also contributing to the ongoing debate on the most appropriate theoretical frameworks for studying agricultural technology adoption.

Chapter 5 integrates and discusses the results of the three previous analyses. The combined use of qualitative and quantitative methods allowed the strengths of each approach to be exploited, providing a richer understanding than could be achieved through a single method.

Chapter 6 draws the main conclusions, outlines the limitations of the research, and suggests directions for future studies. It also highlights the policy implications of the findings, emphasising the need for collaborative strategies that respond to the actual needs of end-users.

Overall, this dissertation is grounded in the opportunities offered by digital technologies to drive agriculture towards greater competitiveness and sustainability. At the same time, it recognises that, despite their potential benefits, the adoption of such technologies remains a complex, context-dependent process that requires targeted and inclusive approaches.

2. Literature review

This chapter reviews the existing literature on the adoption of agricultural technologies in developed countries, with the aim of providing the conceptual foundations for the empirical analyses developed in the subsequent chapters.

The review was designed to identify both the determinants of adoption and the theoretical approaches applied in previous empirical studies, as well as to explore in depth the systemic dimension of the adoption process, which remains comparatively under-researched despite its recognised importance in shaping innovation diffusion (Shang et al., 2021).

Research on agricultural technology adoption has been predominantly conducted in developed countries, with a focus on advanced technologies, whereas studies in developing countries remain relatively scarce (McGrath et al., 2023; Osrof et al., 2023; Shang et al., 2021) and tend to address more basic technologies associated with everyday agricultural activities, often only indirectly linked to the agri-food or industrial sectors. Considering the substantial structural differences between these contexts - such as infrastructure availability, financial resources, and policy frameworks - combining them within the same analytical scope would introduce a significant heterogeneity that could compromise the coherence of the analysis.

Given these conditions, and in light of the fact that the systemic dimension of adoption remains under-researched (Gemtou et al., 2024; Guerrieri et al., 2025), the present study focuses exclusively on industrialised countries, where institutional, economic, and technological conditions allow for a more comprehensive and comparable analysis.

Furthermore, as larger farms are generally more likely to adopt advanced technologies (Kolady et al., 2021), studies on smallholders were also excluded to ensure analytical consistency and comparability.On this basis, the work was conducted in two consecutive stages, employing two distinct review methodologies, to adrees complementary questions. The first stage follows a systematic review logic (predefined search strategy, inclusion/exclusion criteria, and structured data extraction) to map the factors influencing agricultural technology adoption and the theories and models most frequently used to explain it. This step is intended to provide a comprehensive overview of the state of the art in digital technology adoption in agriculture, highlighting recurrent determinants, conceptual frameworks, and existing gaps in current research.

The second stage adopts a scoping review logic (broader and iterative search, flexible inclusion of heterogeneous study types) to specifically map the systemic dimension of adoption, understood as the set of relationships, governance arrangements, market conditions, and institutional frameworks that influence farmers' decisions and the diffusion of innovation across the agri-food system. This perspective moves beyond the individual farm level to consider the wider set of actors, governance structures, institutional arrangements, and market conditions that influence technology uptake (McGrath et al., 2023; Osrof et al., 2023; Sadjadi and Fernández, 2023). The added value of the scoping review is therefore methodological and analytical: it captures dispersed conceptual and operational evidence on the systemic dimension that a strictly systematic review, focused on comparable empirical designs, would likely miss (Levac et al., 2010; Peters et al., 2024).

Importantly, this second stage of literature review builds upon the results of the first general review, which also provided the initial mapping of systemic-related factors and highlighted their underrepresentation in empirical studies. Therefore, the scoping review allowed for a detailed analysis of how these systemic factors have been conceptualised and investigated in the literature, and how they interact with individual adoption decisions.

By combining a general review on factors and theories with a targeted scoping review on the systemic dimension, this chapter establishes a comprehensive analytical framework that underpins the research design of the thesis, ensuring that both individual and systemic determinants are considered in the subsequent empirical work. Specifically, Section 2.1 provides a farm-level factor–theory baseline and identifies gaps in what is repeatedly measured and modelled, while Section 2.2 clarifies how the systemic domain is conceptualised and operationalised across heterogeneous evidence; together, they inform the research questions, the stakeholder interview protocol and coding lenses, and the selection and interpretation of systemic constructs in the farmer survey model.

Therefore, this dual perspective forms the analytical basis for the empirical research presented in the following chapters, ensuring that the adoption model tested in this dissertation is grounded in both established theory and the broader structural context in which farmers operate.

2.1. Factors and theories in agricultural technology adoption

2.1.1 Introduction

The first stage of the literature review aimed to construct a comprehensive state of the art on the process of digital technology adoption in agriculture. This phase was designed to consolidate existing knowledge on both the determinants of adoption and the theoretical frameworks used to explain it, providing a structured basis for the empirical investigations developed in the following chapters.

In line with the overall design of the review, particular attention was also devoted to the systemic dimension of adoption, anticipating its more detailed exploration in the second stage.

Accordingly, the review pursued four objectives:

1. to identify the main factors influencing the adoption of digital technologies in agriculture;
2. to map the theories and models most frequently applied in adoption studies;
3. to group the factors into broader conceptual categories and assess their relative incidence in the literature;
4. to detect the main gaps - particularly regarding the representation and theoretical integration of systemic factors - that still characterise this research field.

Consequently, the review was guided by the following research questions:

1. What are the determinants of digital technology adoption in agricultural farming systems?
2. Which factors act as barriers, and which act as drivers, in this process?
3. To which conceptual categories do these factors belong, and how frequently are they addressed in the literature?
4. What is the relative prominence of the systemic dimension, and to what extent is it theoretically grounded?
5. What are the main theories and models employed to study agricultural technology adoption?

By systematically addressing these questions, the review not only maps the current knowledge base but also directly assesses the representation of systemic factors, thereby laying the groundwork for the second stage of the literature review - a dedicated scoping study on the systemic dimension of adoption in agriculture.

2.1.2 Methodology

A systematic literature review was conducted to identify the factors influencing farmers' adoption of digital technologies in developed countries.

Building on previous systematic reviews (Campuzano et al., 2023; Eastwood et al., 2023; Le Hoang Nguyen et al., 2023; McGrath et al., 2023; Osrof et al., 2023; Sadjadi and Fernández, 2023; Shang et al., 2021; Tey and Brindal, 2022) that informed the empirical scope, search strategy and systemic dimension of adoption, the present study was designed to ensure analytical robustness and comparability. Consistent with the scope defined in the introduction, the review focused exclusively on studies conducted in developed countries and excluded smallholder contexts. This choice was motivated by the substantial structural differences between these contexts in terms of infrastructure, financial resources, and policy frameworks, which could otherwise introduce significant heterogeneity and undermine analytical coherence and comparability.

For inclusion criteria, “developed countries” are operationalised as World Bank high-income economies (i.e., economies classified as high income based on GNI per capita in U.S. dollars, converted using the World Bank Atlas method and updated annually) and comparable advanced agricultural systems (e.g., high mechanisation and market integration). When emerging economies, like Brazil and China, are discussed, this is explicitly motivated by the technological and value-chain relevance rather than by the income-group filter (Rauniyar et al., 2024).

The literature search was limited to studies published from 2020 onwards, following the evidence from prior systematic review (Osrof et al., 2023), highlighting that the discourse on digital agriculture has undergone significant acceleration and conceptual refinement in recent years. Restricting the timeframe allowed the review to capture the most recent technological developments and methodological approaches, thereby reflecting the current state of research and practice in the field. To reduce the risk of omitting foundational contributions, the conceptual background of the thesis also draws on earlier seminal works identified through backward/forward snowballing, while the systematic extraction focuses on the 2020–present core literature.

The validated search strategy combined two thematic blocks of keywords - one describing the technological context (e.g., *precision agriculture*, *digital agriculture*, *smart farming*) and the other referring to the adoption process (e.g., *barrier* to adopt*, *driver* to diffusion*, *adoption* factor*) - connected through Boolean operators. (Table 1):

Table 1 - Key search terms

Technological context	precision agriculture OR precision farm* OR digital agriculture OR smart farm* OR agriculture 4.0 OR smart agriculture
AND	
Adoption process	Barrier* to adopt* OR driver* to diffusion* OR adoption* factor*

The review protocol adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021), ensuring a transparent, rigorous, and reproducible process. The Scopus database was chosen as the primary source due to its extensive coverage of peer-reviewed literature in the agricultural, technological, and social sciences.

Following the PRISMA framework (Figure 2), the study selection proceeded through four main phases.

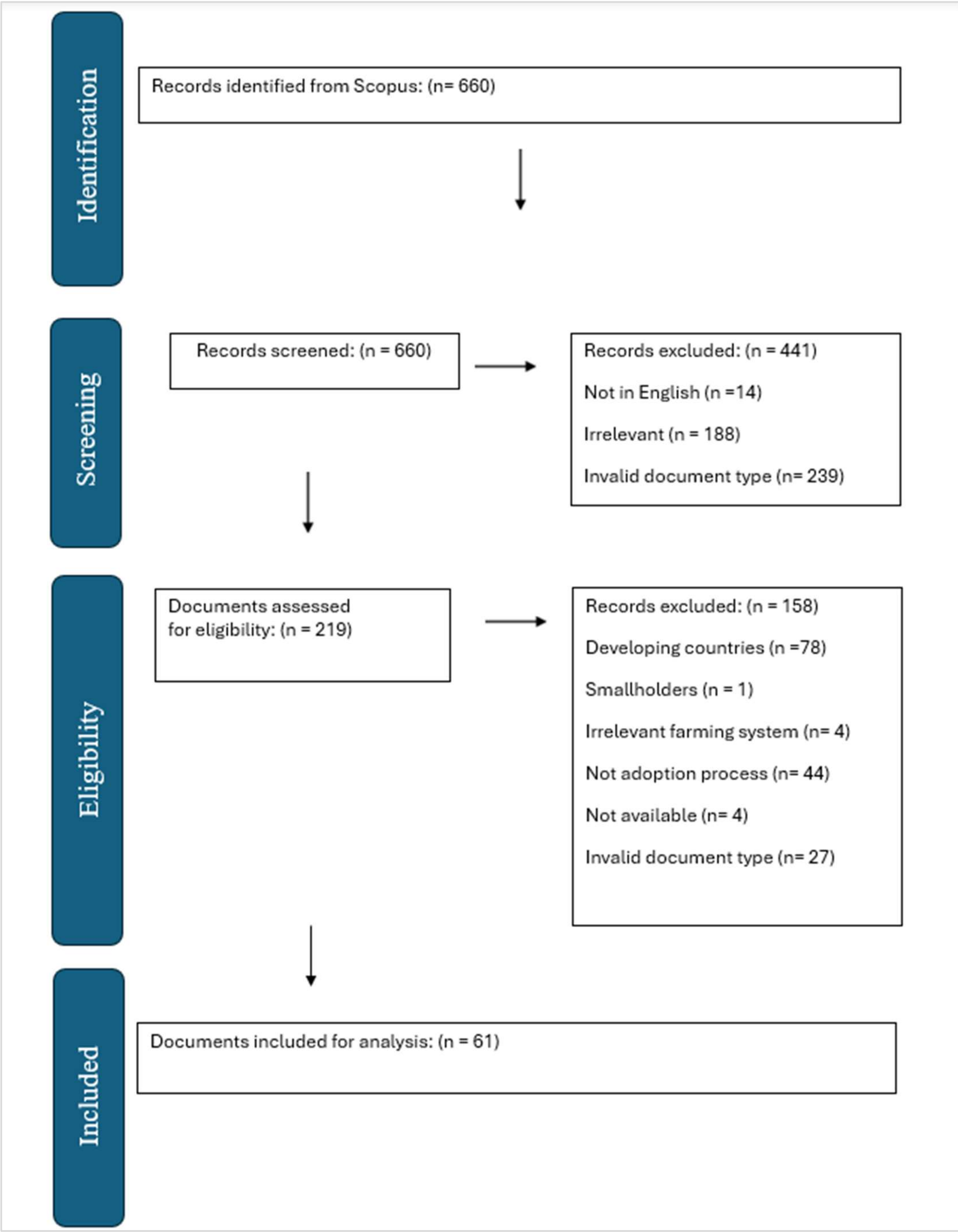


Figure 2 - PRISMA flow diagram

Phase 1: Identification. The initial search in the Scopus database yielded a total of 660 data records, which were subsequently imported into the knowledge management software Zotero.

Phase 2: Screening. As part of the screening process, in-depth filtering was conducted to include the following eligibility criteria (Table 2 - Eligibility criteria Table 2), which refined the scope and resulted in 219 documents that were analysed.

Table 2 - Eligibility criteria

Eligibility Criteria	
Language	English
Documents Types	Original peer-reviewed articles. Prior reviews were excluded as redundant to the present review.
Time reference	From 2020 as literature notably increased.
Mandatory information	• Articles explicitly study the technology adoption process, with a focus on its determinants. Articles that study the adoption of agricultural practices solely were excluded. • Full-text access
Study context	• Developed countries • Not smallholders • All agricultural systems

Using Scopus database filters, the records whose language was not English (14 records) and which represented an invalid document type, as mandatory information setting (239 records) were identified and removed.

In addition, documents dealing with topics related to developing countries, smallholders and non-agricultural systems were also identified by filtering keywords in Scopus database. These articles were marked as irrelevant and excluded, resulting in the removal of a further 188 records.

Phase 3: Eligibility. The titles and abstracts of the 219 documents were independently reviewed based on the following predefined eligibility criteria.

1. Study reporting technology adoption factors;
2. Study relating to the farming system;
4. Study focusing on developed countries;
5. Study without reference to smallholders.

Comparable to the approach of (McGrath et al., 2023), references were excluded if they did not fulfil at least one inclusion criterion. After this phase, 158 studies were excluded due to irrelevance.

Phase 4: Inclusion. 61 studies met the strict criteria for inclusion in the final synthesis and provided robust evidence for the research question under investigation.

The publications screened according to the PRISMA protocol were carefully organized in Excel software to provide an overview of the selected papers, recording descriptive and thematic information on the publications.

The application of content analysis was based on the recommended broad PCC (participant/concept/context) framework (Figure 3) to properly narrow down the main concepts of the review questions (Peters et al., 2024).

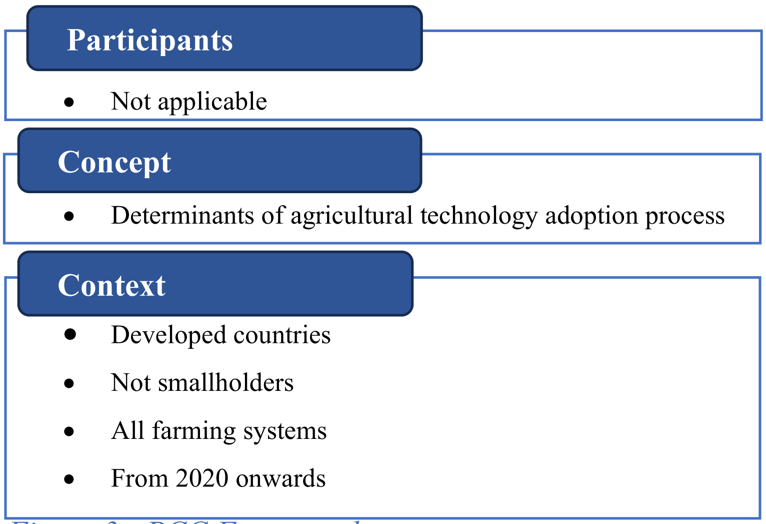


Figure 3 - PCC Framework

To provide a comprehensive overview of how agricultural technology adoption has been investigated in the literature, the research design and methodological approach were identified for each of the 61 selected articles. The analysis covered the following thematic dimensions: (1) the geographical scope of the study; (2) the research methodology employed; (3) the theoretical or conceptual framework adopted; (4) the type of participants involved; (5) the farming system considered; and (6) the specific technology or tool under investigation.

Finally, to provide a complete overview of the agricultural technology adoption process in the literature, all determinants of adoption (drivers and barriers) were extracted from the selected studies (n =61).

These factors were then cleaned of duplicates and aggregated based on the similarities identified in their individual descriptions, with a final harmonised description developed for each aggregated factor to ensure conceptual clarity and consistency across the dataset. The full list of drivers and barriers is provided in the supplementary materials.

Following prior relevant reviews (Osrof et al., 2023; Shang et al., 2021), adoption factors were properly classified into five categories: Individual, External, Organizational, Technological, and Institutional.

Furtheremore, to assess the presence and treatment of the systemic dimension in the reviewed literature, the adoption factors identified were reclassified according to the following operational definition:

"The set of relationships and interactions among actors in the agricultural system (e.g., farmers, suppliers, advisors, cooperatives, institutions, markets) and infrastructures that influence the diffusion and integration of technological innovations, encompassing technical, economic, social, and regulatory aspects in an interconnected perspective" (McGrath et al., 2023; Osrof et al., 2023; Sadjadi and Fernández, 2023).

A set of descriptive measures was applied to translate qualitative evidence into comparable indicators, following common practice in bibliometric analyses (Marzi et al., 2025). This approach enabled a transparent evaluation of the prominence, empirical weight, and theoretical grounding of agricultural adoption factors.

For every factor, two metrics were calculated: (1) Number of unique articles, mentioning the factor obtained by parsing and counting unique references; (2) Theory frequency – the proportion of articles mentioning the factor that also reported an explicit theoretical framework.

These metrics were aggregated for systemic and non-systemic factors to enable comparison across three analytical dimensions: (1) Coverage, evaluated by the share of systemic factors over total factors and share of article mentions of systemic factors over total mentions; (2) Empirical weight, evaluated by the average number of articles per factor in each group (systemic vs. non-systemic), to assess whether systemic factors are empirically more or less represented; (3) Theoretical framing, evaluated by the average theory frequency for systemic and non-systemic factors, to evaluate the degree of conceptual grounding.

By combining these measures, it was possible to determine whether the systemic dimension was marginal (low share of factors and mentions), fragmented (lower empirical weight), and/or lacking in theoretical coherence (lower theory frequency).

2.1.3 Results

The systematic literature review included a total of 61 peer-reviewed scientific contributions addressing the adoption of digital technologies in agriculture, spanning a range of methodological approaches, geographical contexts, and technological focuses, providing a comprehensive, yet heterogeneous representation of the research landscape in this field (Table 3).

Table 3 - Summary of the studies

Indicator	Value
Total articles	61
Years covered	2020–2023
Geographical Area	United States: 14 Europe: 9 Italy: 9 Others: 27 Worldwide: 2
Methodology	Quantitative: 67.2% (41) Qualitative: 31.1% (19) Mixed: 1.6% (1)
Main Tool/Approach	Quantitative: Questionnaire (83%) Others (17%) Qualitative: Interview (37%) Multiple (32%) Others (31%) Mixed: Survey and interviews (100%)
Theories/Models	No reference 32 (52.5%) TPB 7 (24.1%), DOI 5 (17.2%) TAM 3 (10.3%), RUM 3 (10.3%) Mixed 3 (10.3%), Others 8 (27.8%)
Participant type	Single actor: 72.1% (44) Multi-actor: 27.9% (17)
Farming system	Generic: 55.7% (34)

	Crop-specific: 36.1% (22) Horticulture: 1.6% (1) Livestock: 3.3% (2) Viticulture: 3.3% (2)
Technology focus	General: 51% (31) Specific: 49% (30)

Years covered

The development of publications reveals a generally upward trend in interest on digital technology adoption in agriculture. The number of studies grew from 16 in 2020 to 18 in 2023, with a temporary drop to 10 in 2021 followed by a sharp recovery to 17 in 2022 (Figure 4).

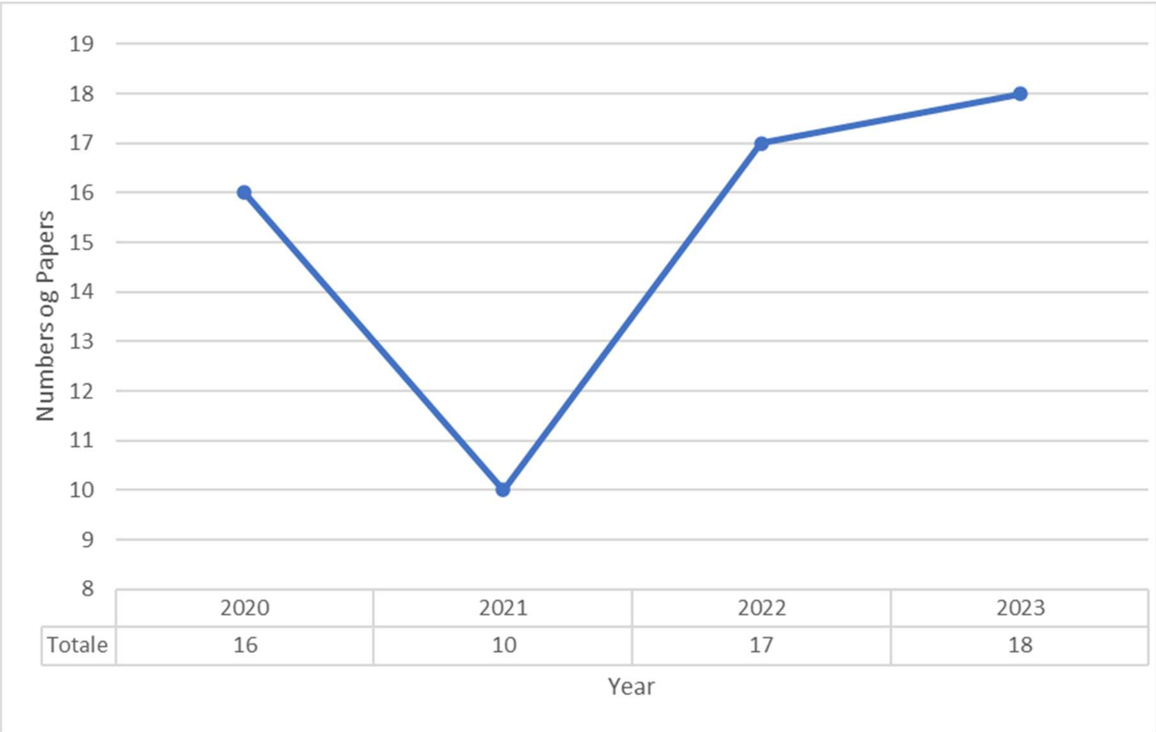


Figure 4 - Number of papers per year (source: our elaboration)

This pattern indicates that scientific interest in the adoption of digital technologies in agriculture has remained consistently high and stable, consistent with previous literature reviews that have identified a consolidated trend of growing research in this area (Osrof et al., 2023).

Geographical Area

In total 16 countries represent the nationality of the studies. For clarity, only those countries that produced more than one study are shown in Figure 5. In addition, articles from China were also included in the analysis as China is the dominant country leading the global supply chain and is considered the largest manufacturing economy in the world (Rauniyar et al., 2024).

The geographical distribution of publications reveals a marked concentration in a limited number of national and regional contexts. The United States emerges as the leading contributor with 14 studies, followed by Italy and Europe (9 studies each), while Australia maintains a significant presence with 7 publications. Germany occupies an intermediate position with 5 studies, whereas Brazil and China show more limited representation (3 studies each). Only a small proportion of works (2 studies) adopt a global perspective, addressing the adoption of digital technologies in agriculture at an international scale rather than within a single national context. This pattern highlights the prominence of specific national and regional contexts in shaping the evidence base on digital technology adoption in agriculture, with research efforts clustering in countries that combine advanced technological capacity, strong research networks, and established agricultural sectors.

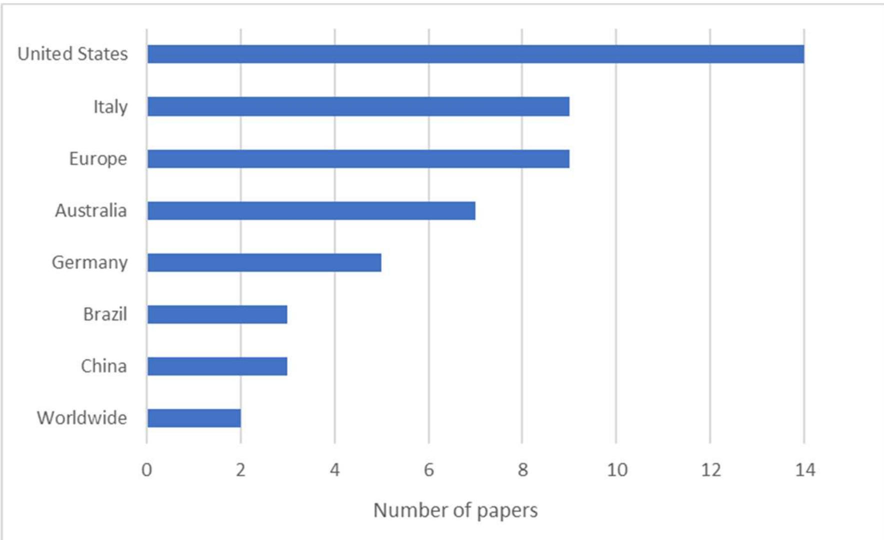


Figure 5 - Geographical distribution of the studies (source: our elaboration)

Methodology and Main Tool/Approach

From a methodological perspective, most of the studies were empirical in nature, with quantitative methods dominating the sample and accounting for 67.2% of contributions.

Building on this distribution, a closer inspection of methodological choices reveals a strong predominance of survey-based designs within the quantitative category, with questionnaires alone accounting for 55.7% of all studies and representing the vast majority of works in this group (83%). More sophisticated quantitative approaches, such as agent-based modelling, the evolutionary game model, and metric-based analyses, were comparatively rare and appear to be employed only in highly specific research contexts. Discrete Choice Experiments, also classified under the quantitative domain, accounted for 4.9% of the total sample, further reinforcing the centrality of structured, respondent-based data collection in the field.

Within qualitative research (31.1%), interviews emerged as the most widely used method 37%, representing 11.5% of all studies and underscoring the importance of capturing in-depth perspectives and contextual nuances in understanding technology adoption. Multi-method qualitative designs (Padyab et al., 2020; Tran et al., 2023) accounted for 9.8%, indicating an effort by some scholars to triangulate insights from different sources. Other qualitative techniques, such as case studies, co-design processes, focus groups, and SWOT analyses, were present but accounted for a smaller share of the literature, often serving as exploratory tools or complementary components within broader research designs.

Mixed-methods studies were almost absent from the reviewed corpus, with only one contribution (Khalsa et al., 2022), suggesting that the integration of quantitative breadth with qualitative depth remains underutilized in this research domain. Similarly, Delphi studies—valued for their ability to build expert consensus—were adopted in just one case (Ammann et al., 2022), appearing only in isolated contexts.

This methodological landscape highlights a clear preference for approaches that enable large-scale generalization, while more interpretive and participatory designs remain relatively marginal. Such an imbalance suggests opportunities for future research to diversify methodological strategies, particularly by increasing the use of mixed methods and participatory approaches to better capture the multi-dimensional and systemic nature of digital technology adoption in agriculture.

Theory/Model

A critical pattern emerging from the review concerns the limited and uneven use of theoretical frameworks. Over half of the studies (52.5%) did not explicitly reference any theory or conceptual model, instead relying on descriptive or exploratory analyses without a guiding interpretative lens. When theoretical foundations were employed, the most frequent reference was to the Theory of Planned Behaviour (TPB) (24.1%) followed by the Diffusion of

Innovations (DOI) theory (17.2%), and the Random Utility Model, Technology Acceptance Model (TAM) and Mixed-methods (10.3%). Other models such as the Unified Theory of Acceptance and Use of Technology (UTAUT), the Trans-theoretical Model (TTM), the Multi-level Perspective (MLP), the FACOPA model, and the AKAP model, each appeared in only 1.6% of the cases.

A closer examination of the methodological distribution reveals that qualitative studies, exhibited an even more fragmented theoretical foundation, with references dispersed across a wide range of models and many studies lacking any explicit theoretical framing. In these cases, theories tended to be applied in a context-specific manner—often as interpretative tools for analysing local adoption processes—rather than as part of a broader, systematic conceptual framework. Notably, quantitative studies—despite representing 67.2% of the empirical works—displayed the lowest rate of theoretical grounding, reinforcing the impression that the field prioritises empirical description over theory-driven hypothesis testing and model validation.

Participant types

In terms of study participants, single actors were by far the most represented group featuring 72.1% of the reviewed studies. Among these, farmers were the most represented type of participants, covering the 84.1% of the category. Other categories, such as advisors, cooperatives, extension professionals, experts, and researchers, appeared only sporadically. A smaller but still relevant share of contributions involved broader stakeholder groups, including retailers and suppliers (1.6%) (Mitchell et al., 2021), general stakeholders (8.2%) (Masi et al., 2022; Vecchio et al., 2022a), and mixed categories such as farmers combined with agricultural experts, firms, or consultants. The presence of these multi-actor configurations, which together accounted for a notable portion of the sample, reflects recognition that the adoption of digital technologies in agriculture is influenced by interactions within broader innovation systems and value chains. Nevertheless, this systemic framing remains secondary to farmer-centric designs, indicating that research on digital technology adoption continues to be strongly oriented towards the individual decision-making processes of primary producers.

Farming systems

Regarding the farming systems investigated, the majority of studies (54.1%) adopted a generic perspective, addressing adoption issues without reference to a specific crop or production system. Among those with a defined focus, crop production emerged as the most represented category (21.3%) (Anastasiou et al., 2023; Wang et al., 2023), followed by irrigated systems (6.6%) (Zuo et al., 2021) and cotton production (3.3%) (McDonald et al., 2022). Other contexts, such as viticulture (3.3%), and others (<2%) were far less frequent, highlighting their marginal presence in the literature. The predominance of generic approaches suggests that much of the research aims to identify cross-cutting adoption patterns, while sector-specific analyses remain limited, potentially constraining the understanding of adoption dynamics in specialized or niche agricultural systems.

Technology focus

The technological scope covered in the reviewed literature showed a balanced distribution between generalist and specific approaches. General framing accounted for 51.0% of studies, often using umbrella terms such as "Smart farming" or "Digital agriculture" or "Precision agriculture" without focusing on a single technology. The remaining 49.0% targeted specific domains, with Climate-smart practices (Johnson et al., 2023; Pagliacci et al., 2020) and Unmanned aerial vehicles (UAVs) each appearing in 6.6% of contributions. Other notable focuses included Internet of Things (IoT) (4.9%), Variable rate technology (VRT) (4.9%), Water management (4.9%), and Farm management information systems (FMIS) (3.3%). Marginal interest scored studies on Information and communication technologies (ICT) (3.3%), Enterprise resource planning (ERP) systems (1.6%), and Robots (1.6%). While generalist perspectives facilitate the identification of broad adoption trends, they may limit the generation of technology-specific insights, potentially hindering cross-study comparability.

Content analysis

The consolidated screening of the literature identified 63 adoption factors, grouped into five main categories: individual, external, organisational, technological, and institutional (Osrof et al., 2023; Shang et al., 2021). The distribution revealed a clear predominance of individual-level determinants (46.0% of all distinct factors), which include elements such as attitudes, skills, and perceptions. These were followed by external factors (22.2%), while organisational (15.9%), technological (9.5%), and institutional (6.3%) factors appeared less frequently, both in terms of the diversity of distinct factors and the number of article mentions (Table 4)

In terms of article mentions, the analysis revealed a comparable distribution of factors categories to numbers of factors, confirming that research on the adoption of digital technologies in agriculture is overwhelmingly concentrated on the characteristics and behaviours of individual actors, with external conditions, many of which are systemic, playing a secondary but non-negligible role.

Table 4 - Factors distribution among categories (source: our elaboration)

Category	Distinct factors (N)	Distinct factors (%)	Article mentions (N)	Article mentions (%)	Systemic incidence (%)
Individual	29	46.0	161	41.8	0.0
External	14	22.2	82	21.3	68.7
Organizational	10	15.9	44	11.4	6.2
Technological	6	9.5	71	18.4	6.2
Institutional	4	6.3	27	7.0	18.7
Total	63	100	385	100.0	100

The analysis of the frequency of adoption factors identified in the literature reveals a nearly balanced distribution between drivers (51.9% of mentions) and barriers (44.2%), with a small share of barrier/driver factors (3.9%), that is, elements whose role can shift depending on the context or stakeholders' perception (Table 5).

Among drivers, the largest share comes from individual factors (23.4%), followed by external elements (14.5%), organizational factors (7.0%), and, to a lesser extent, institutional (3.9%) and technological (3.1%) factors

Table 5 - Distribution of factors by category and role

Category	Driver (%)	Barrier (%)	Barrier/Driver (%)	Total (%)
Individual	23.4	18.2	–	41.6
External	14.5	7.0	–	21.5
Organizational	7.0	0.5	3.9	11.4
Technological	3.1	15.3	–	18.4
Institutional	3.9	3.1	–	7.0
Total	51.9	44.2	3.9	100.0

Among the drivers, the most frequently mentioned is perceived usefulness and benefits (11.5%), followed by farm size (9.5%), education and training (6.5%), financial and institutional support (6.5%), and attitude towards innovation (6.0%) (Table 6). These results appear to highlight the decisive weight of farmers' perceptions and farm-level capacities, as well as the importance of human capital and institutional support.

Barriers show a different profile: the largest share relates to technological (15.3%) and individual (18.2%) factors, while external (7.0%), institutional (3.1%), and organizational (0.5%) components are less frequently mentioned. The main barriers identified are high investment cost (13.5%), age (9.4%), compatibility and interoperability (8.8%), lack of infrastructure (8.2%), and lack of knowledge and awareness of technology (6.5%). These findings confirm that, alongside economic and infrastructural constraints, significant obstacles remain related to training, experience, and individual predisposition toward innovation.

Finally, barrier/driver factors (3.9%) are exclusively related to the organizational sphere and include elements such as farm location and region, farm characteristics, farming system, and farm management type. Their dual nature shows that the impact of these factors is highly context-dependent, shaped by production systems, local conditions, and operational settings.

Table 6 - Top-5 factors for each role (share of total mentions)

Driver (51.9%)	%	Barrier (44.2%)	%
Perceived usefulness and benefits (Individual)	11.5	High investment cost (Technological)	13.5
Farm size (Organizational)	9.5	Age (Individual)	9.4
Education and training (External)	6.5	Compatibility and interoperability (Technological)	8.8
Financial and institutional support (Institutional)	6.5	Lack of infrastructure (Technological)	8.2
Attitude towards innovation (Individual)	6.0	Lack of knowledge & awareness of technology (Individual)	6.5

The ranking of factors by role reveals a marked symmetry between drivers and barriers in terms of both thematic focus and category distribution. This distribution suggests that the literature tends to emphasise both enabling conditions with positive determinants of adoption and obstacles.

Among the drivers, the top positions are dominated by Individual and External factors, notably Perceived usefulness and benefits (Individual, 6.0% of total mentions), Farm size (Organisational, 4.9%), and Education and training (External, 3.4%). Institutional support also emerges prominently through Financial and institutional support (3.4%). Other recurrent drivers include attitudinal and behavioural aspects (Attitude towards innovation, Perceived behavioural control, Trust in technology system) alongside relational/systemic dimensions (Subjective norm, Social interactions, Access to technical support). Technological attributes are less frequently cited among the top drivers, with Ease of use (2.1%) being the most prominent.

Barriers, on the other hand, show a strong concentration in the Technological and Individual categories. High investment cost (Technological, 6.0%) is the most cited barrier, followed by Age (Individual, 4.2%) and Compatibility and interoperability (Technological, 3.9%). Other significant technological constraints include Lack of infrastructure (3.6%) and Complexity of technology (1.8%). On the individual side, Lack of knowledge and awareness (2.9%) and Technology competence (2.6%) rank highly, highlighting the role of human capital limitations in slowing adoption. Systemic barriers—such as Facilitating conditions (External, 2.3%) and Lack of information (External, 1.8%)—are comparatively less frequent but point to structural issues in support systems and information flows.

From a category perspective, the distribution confirms the findings of the broader factor analysis: the Individual dimension dominates among drivers, whereas barriers are more evenly distributed between Technological and Individual constraints. External and Institutional categories appear in both roles, but with a lower share of mentions, indicating that systemic or policy-related factors—although present—are not the central focus of most empirical studies. Organisational factors occupy an intermediate position, with Farm size emerging as a particularly relevant determinant in both enabling and constraining roles.

Overall, this dual ranking underscores two key insights. First, the literature still privileges individual-level determinants, especially when framing the adoption process in positive terms (drivers), while systemic and structural barriers receive less emphasis. Second, technological constraints remain a major bottleneck, suggesting that, despite the potential of digital innovations, technical feasibility and usability issues continue to be critical obstacles to widespread adoption. This pattern reinforces the importance of integrating both human capital development and systemic support mechanisms into strategies aimed at accelerating the digital transition in agriculture.

A specific focus was placed on the systemic dimension, operationally defined as the set of relationships and interactions among actors (farmers, advisors, cooperatives, institutions, markets) and infrastructures that influence the diffusion and integration of technological innovations, encompassing technical, economic, social, and regulatory aspects in an interconnected perspective (McGrath et al., 2023; Osrof et al., 2023; Sadjadi and Fernández, 2023).

Of the 63 factors identified, 16 (25.4%) were classified as systemic (Table 7). Their examination revealed that they were addressed in a comparatively smaller number of studies than non-systemic factors, with 61 out of the 385 total article mentions (24.9%). This confirms that their representation within the literature remains limited.

Finally, only 25.8% of the mentions of systemic factors were linked to an explicit theoretical framework, compared to 26.8% for non-systemic factors. This suggests that both categories suffer from a relatively low level of theoretical anchoring, although the difference between them is minimal.

Table 7 - Systemic factors summary (source: our elaboration)

Metric	Value
Systemic factors (N)	16
Incidence of systemic factors (%)	25.4
Total article mentions (N)	Systemic: 96 All factors: 385
Incidence of systemic mentions (%)	24.9
Average articles mentions	Systemic: 6.0 Non-systemic: 6.15
Theory coverage (%)	All factors: 47.5 Systemic: 25.8 Non-systemic: 26.8

Overall, these findings point to a twofold gap: first, the systemic dimension receives limited attention in terms of both the number of factors addressed and the empirical studies in which they appear; second, it is infrequently anchored to established theoretical models, which constrains the development of an integrated understanding of how systemic interactions shape technology adoption.

A comparison of systemic and non-systemic factors on two additional dimensions reveals that, in terms of average number of articles per factor, systemic factors are discussed in 6,0 studies on average, compared to 6.15 for non-systemic factors—indicating a similar empirical density per factor. In terms of theoretical framing, the coverage is also very close (25.8% vs. 26.8%), confirming that systemic determinants, while less numerous and less mentioned overall, are treated with a comparable degree of theoretical explicitness to non-systemic ones.

The results of the general literature review confirmed a marked imbalance in the treatment of determinants of digital technology adoption in agriculture. Individual-level factors—such as attitudes, skills, and perceptions—predominated, while systemic factors, encompassing relationships among actors, governance arrangements, market structures, and institutional frameworks, were comparatively underrepresented.

Given the central role that systemic interactions can play in enabling or constraining technology uptake, this underrepresentation represents a significant knowledge gap. Addressing it is essential to developing an integrated understanding of adoption processes that goes beyond the individual decision-making perspective.

This combination of (i) empirical underrepresentation, (ii) limited theoretical anchoring, and (iii) the strategic importance of systemic conditions for technology diffusion, provided the rationale for conducting a dedicated scoping review. The objective of this second stage of the literature review was therefore to map how the systemic dimension has been conceptualised, categorised, and empirically investigated in studies of agricultural technology adoption, thus filling a critical gap in the current evidence base and informing subsequent empirical phases of this research.

2.2. Adoption of innovative technologies for sustainable development in agriculture: A scoping review of the system domain

2.2.1. Introduction

Building on the general literature review presented in Chapter 2.1, which mapped the determinants of digital technology adoption and the theoretical frameworks most frequently employed, this section focuses specifically on the systemic domain of adoption. The general aim is to clarify how the systemic dimension has been conceptualised, operationalised, and empirically investigated in the context of developed countries.

In line with the definition anticipated in the Background and motivation (Chapter 1.1) and further discussed in the general introduction of the literature review (Section 2.1.1), the systemic dimension is understood as the network of relationships, governance arrangements, and enabling infrastructures that shape technology uptake. It is characterised by interactions among farmers, cooperatives, advisors, technology providers, supply chain actors, and institutions, together with rules, norms, incentives, and data-sharing mechanisms that enable or constrain diffusion. This perspective recognises that adoption is not solely the outcome of individual attitudes or farm-level characteristics, but rather the result of interdependencies such as knowledge circulation, alignment of intentions, and capacity building.

Nonetheless, several issues justify a targeted investigation. As highlighted in the results of the general literature review (Section 2.1.3), systemic factors have so far received limited empirical coverage. They are often addressed only narratively, with blurred conceptual boundaries (e.g., "facilitating conditions," "institutional support," "cooperation"), and with weak theoretical anchoring that hampers cumulative evidence and its translation into policy or practice.

For these reasons, and consistent with the analytical scope previously defined, the present section adopts a scoping review approach. This design enables:

1. to assess the extent and diversity of coverage of systemic factors in existing research;
2. to identify the interactions between systemic characteristics and the process of technology adoption;
3. to detect gaps in the literature related to the systemic dimension of agricultural technology adoption.

To ensure comparability with the subsequent empirical analyses in Chapter 3, the review is restricted to industrialised countries and explicitly excludes smallholder contexts, where structural, institutional, and market conditions differ substantially. In doing so, the section fulfils a dual function: first, it documents the imbalance between individual and systemic determinants; second, it establishes the conceptual bridge with the empirical part of the dissertation, informing both the design of Section 3.1 and the operationalisation of systemic constructs in the extended behavioural model tested in Section 3.2.

In order to achieve these objectives, the following key research questions were formulated:

1. To what extent, and in what variety, are systemic factors addressed in the existing research literature in developed countries? How have they been defined and treated?
2. What are the interactions between systemic characteristics and the process of technology adoption in developed countries?
3. What are the key systemic determinants of innovative technology adoption in developed countries?
4. What are the main gaps in the literature regarding the systemic dimension of adoption?

The work carried out in this section has also led to a scientific publication (Addorisio et al., 2025b)

2.2.2. Methodology

A literature review was conducted on the systemic factors that influence the adoption of innovative technologies by farmers.

Following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) extension protocol for scoping reviews by (Tricco et al., 2018), the analysis ensured a rigorous and reproducible process for the selection of suitable articles from the Scopus, Web of Science, Google Scholar and Semantic scholar databases. This protocol allows the inclusion of academic publications such as scientific articles, book chapters, conference proceedings and reviews as well as grey literature reports and documents. Given the different methodological approaches in the existing literature, it is important to ensure a comprehensive understanding of the topic (Davis et al., 2009).

To specifically capture the role of the system dimension in the process of technology adoption, a two-step analysis procedure was conducted, similar to other authors (Siminiuc et al., 2025). In the first step, a quantitative analysis of all selected documents (n = 151) was performed using bibliometric network analysis and thematic analysis. The bibliometric network analysis made it possible to examine the frequency and co-occurrence of keywords in the selected articles, thereby identifying the main concepts and thematic clusters that represent the main drivers of technology adoption in agriculture.

The thematic analysis provided descriptive information about the research design and methods employed in the reviewed literature, while also allowing a deeper understanding of the overall context.

In the second step, the most important articles were selected and analysed in detail through content analysis. Consistent with the objective of exploring the systemic dimension of agricultural technology adoption, the selection of relevant articles was guided by the inclusion of stakeholders as study participants, since this criterion reflects the systemic nature of the adoption process, characterised by the interaction of multiple actors. Consequently, only studies in which stakeholders were directly involved were considered for the subsequent qualitative analysis, resulting in 28 articles (Addorisio et al., 2025b) subjected to in-depth examination. A comprehensive data extraction form was developed to guide the content analysis of the full articles.

This approach made it possible to identify both the key determinants of technology adoption and the underlying relationships between individual decisions and overall system dynamics in agricultural systems. Moreover, it provided a comprehensive overview of how the systemic dimension has been conceptualised and developed in the literature over time.

Data sources and research strategy

In order to systematically search the literature, a two-stage document search was carried out. In the first phase, keywords were selected on the basis of insights from the previously reviewed literature. The bibliometric search was conducted from a systems perspective and focused on identifying keywords relevant to the research area, such as “system interactions”, “holistic approach”, and “stakeholders’ involvement”, in order to ensure consistency with the scope of the study.

The second phase of the search was guided by the recommended PCC (participant/concept/context) framework (Figure 6), which helped to narrow down the main concepts addressed by the review questions, specifically mapping the systemic scope of factors influencing farmers’ adoption of innovative technologies (Peters et al., 2024). This step also enabled the exclusion of documents that did not address the guiding questions.

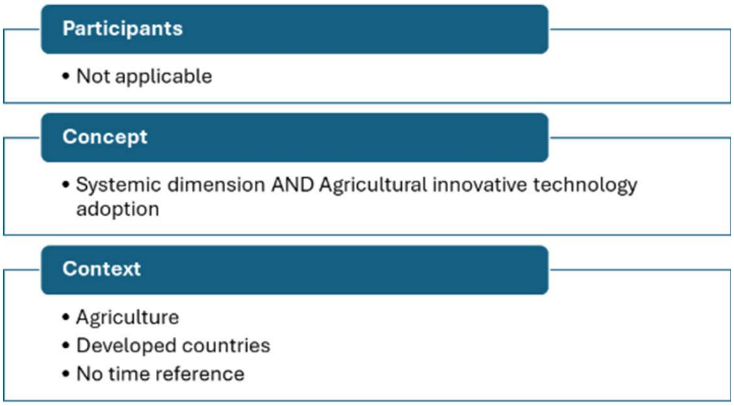


Figure 6 - PCC Framework

The search strategy was designed to capture the systemic dimension of the technology introduction process. To properly outline this dimension in the research context, the most relevant literature on the determinants of agricultural technology adoption was first examined in order to build a comprehensive body of knowledge. The review was conducted through a systematic process to ensure a thorough and consistent approach. A set of terms corresponding to systemic factors was defined and used to search scientific databases between February and March 2025. The final validated search query employed for the literature review is reported in Table 8 - Key search terms .

Table 8 - Key search terms

Technological context	precision agriculture OR precision farm* OR digital agriculture OR smart farm* OR agriculture 4.0 OR smart agriculture
AND	
System domain	training OR education OR infrastructure OR competitive pressure OR market OR financial support OR labor OR technology usability OR attractiveness OR appeal OR farming system OR cropping system OR stakeholders engagement OR stakeholders involvement OR events OR cooperation OR information sources OR institutions OR workshops OR regulations OR policy OR governance OR subsidies OR data privacy OR data security OR subjective norms OR technical

	support OR consultants OR advisors OR advisory service OR service sources OR extension services
AND	
Process	tech* adoption* OR tech* diffusion* OR tech* uptake OR tech* implementation

Study selection

According to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) extension protocol for scoping review (Tricco et al., 2018), shown in Figure 7, the study selection included four main phases.

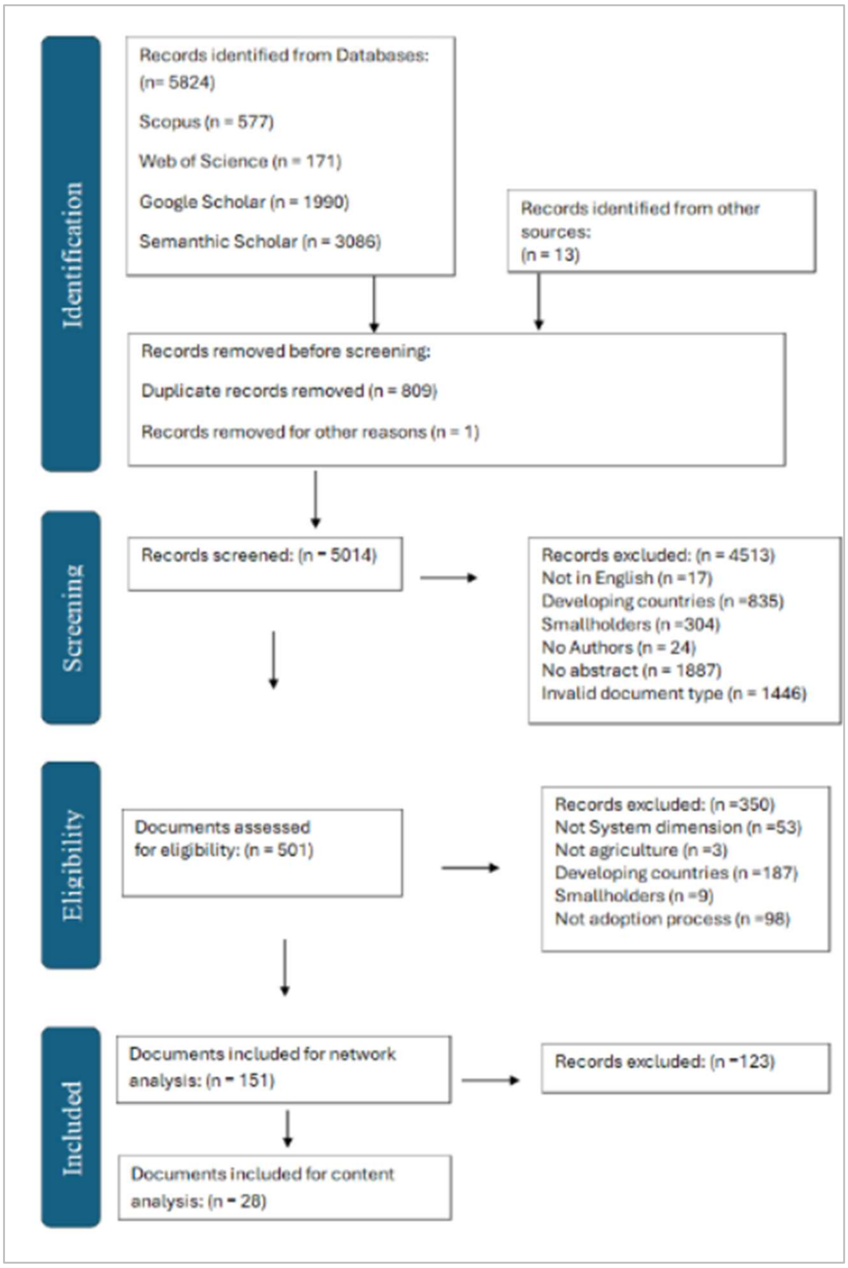


Figure 7 - PRISMA flow diagram

Phase 1: Identification. The initial search in the selected databases yielded a total of 5824 records, which were then imported into the knowledge management software Zotero. In addition, 13 key sources on the introduction of agricultural technologies, previously used to inform the background and methodology, were also included. After the removal of 809 duplicates through automatic and manual deduplication techniques, and the exclusion of one document withdrawn from publication, 5014 unique records remained for screening.

Phase 2: Screening. In the screening stage, records were filtered according to predefined eligibility criteria (Table 9). This refinement of the scope resulted in 501 documents that were retained for further analysis.

Table 9 - Eligibility criteria

Eligibility Criteria	Peer reviewed literature	Grey literature
Language	English	English
Documents Types	All	Journal articles, conference papers
Mandatory information	Authors, title, abstract	Authors, title, abstract
Study context	Developed countries Not smallholders	Developed countries Not smallholders

Non-English records (17) and invalid document types (1446) were first excluded. Documents focusing on developing countries were identified through keyword searches in the title and abstract (e.g., "developing country", "low income", "emerging country") and subsequently removed, resulting in the exclusion of 835 records. A further keyword-based search identified documents on small-scale farming systems; articles containing the term "smallholder farmers*" were assessed and, where appropriate, removed (304 records). Finally, records without identified authors (24) and those lacking an abstract (1887) were excluded.

Phase 3: Eligibility. The titles and abstracts of the remaining 501 documents were reviewed against the definition of key terms and the eligibility criteria:

1. study on the process of technology adoption;
2. study on the agricultural sector;
3. study that considers, among other aspects, the systemic dimension of the adoption process;
4. study focusing on developed countries;
5. study with complete bibliographic reference.

Following an approach similar to (McGrath et al., 2023), records not meeting at least one criterion were excluded. At this stage, 350 studies were removed due to irrelevance.

Phase 4: Inclusion. A total of 151 studies fulfilled the inclusion criteria and were retained for the final quantitative synthesis (network analysis), providing robust evidence to address the research questions. From these, 28 articles were identified as the most relevant and subjected to in-depth content analysis.

Data extraction and analysis

The bibliometric network analysis was employed to identify the network of relationships between systemic factors influencing the adoption of innovative technologies in agriculture. This method allowed for a quantitative assessment of research trends, co-occurrence patterns, and conceptual linkages in the literature, ensuring a structured understanding of the systemic dimension of technology adoption.

All publications screened according to the PRISMA-Scr protocol were organized in Excel to compile an overview of the selected studies, including titles, authors, journals, and year of publication. Subsequently, VOSviewer (Waltman et al., 2010) was used to perform a network analysis of titles, abstracts, and keywords. VOSviewer is a widely used tool for bibliometric analysis across various disciplines, including agricultural sciences. It is particularly effective for constructing and visualizing bibliometric networks, mapping co-occurring keywords, and identifying thematic clusters (Maesano et al., 2022; Van Eck and Waltman, 2018).

The software also enables the exploration of relationships between authors, institutions, and research topics, highlighting influential contributions and emerging areas of interest.

In this study, a co-word analysis was conducted to identify major themes and concepts by examining the frequency of keyword co-occurrence. To ensure consistency, the dataset was pre-processed by normalizing keywords and author names. The following parameters were applied: “map based on bibliographic data”, “co-occurrence” as the analysis type, “keywords” as the unit of analysis, “full count” as the counting method, and a minimum threshold of six co-occurrences to highlight the most significant nodes. The “total number of elements” was set to define the full scope of information considered.

The visualization features of VOSviewer were used to generate graphical representations in which node size reflected the frequency of occurrence and edge thickness reflected the strength of associations. The density visualization further enabled the identification of research hotspots by displaying areas of intense keyword activity.

By applying this bibliometric approach, the underlying structure of research on systemic factors in agricultural technology adoption was revealed, allowing the identification of knowledge gaps and emerging trends. The combination of these analytical techniques ensured a systematic, reproducible, and objective synthesis of the literature, strengthening the methodological rigour of the study.

To extend the bibliometric network analysis, thematic clusters based on co-authorship were also generated and analysed. Complementarily, thematic analysis was applied to integrate the bibliometric findings and provide a complete overview of how the systemic dimension has been treated in the literature. For each selected article, descriptive information was extracted regarding: (1) the technology or tool investigated; (2) the theoretical or conceptual framework adopted; (3) the research methodology; (4) the type of participants involved; (5) the farming system considered; and (6) the geographical context.

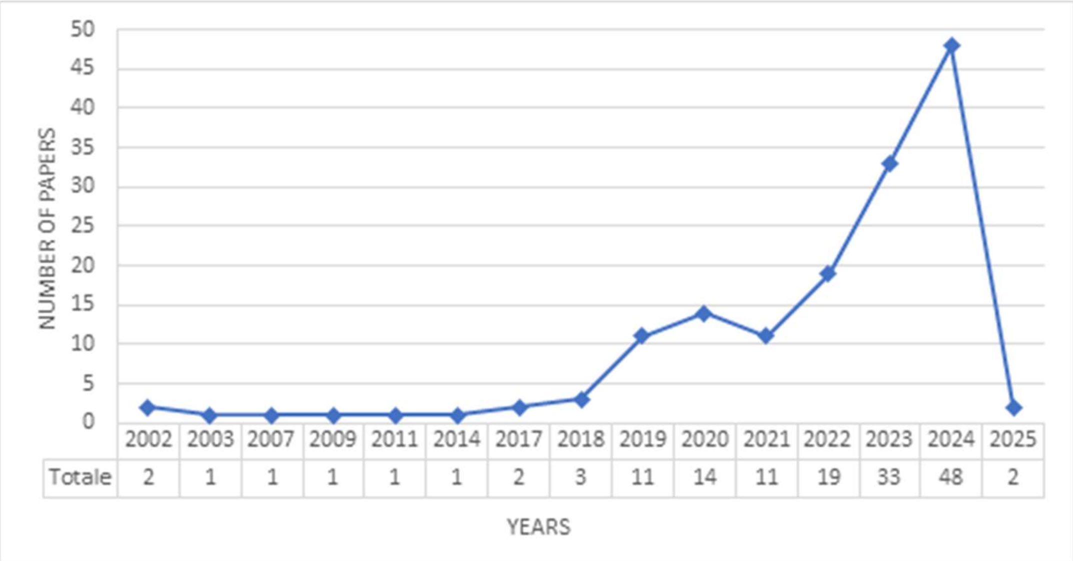
Finally, the most relevant articles were fully reviewed and analysed in depth using the data extraction form (Appendix 2) to examine how the systemic dimension of agricultural technology adoption has been defined and developed in the literature.

2.2.3. Results

Bibliometric analysis

The development of publications indicates that research interest in the topic has steadily increased over time. Between 2002 and 2014, the number of publications remained low and relatively stable. A gradual increase began in 2017, followed by a marked rise from 2019 onwards, with the majority of studies (67%) published between 2022 and 2024 (Figure 8).

The data for 2025, which includes only two publications, reflects the first two months of the year and is therefore not representative of the overall trend. Taken together, these findings suggest that the topic has gained growing scientific attention in recent years, particularly since 2019, with a noticeable increase in the number of contributions.



	2002	2003	2007	2009	2011	2014	2017	2018	2019	2020	2021	2022	2023	2024	2025
Totale	2	1	1	1	1	1	2	3	11	14	11	19	33	48	2

Figure 8 - Number of Papers per Year (Source: author's elaboration)

In total, thirty-three countries represent the nationality of the authors. For clarity, only those countries that produced more than one study are shown in Figure 9. The geographical distribution of academic documents shows a strong concentration in a few countries, with Europe leading with 64 publications, especially Italy (19) and Germany (11), followed by the United States with 24 publications. This distribution reflects the strong scientific research infrastructure of developed countries, with other countries such as India (10), Australia (9) and China (6) reinforcing this pattern.

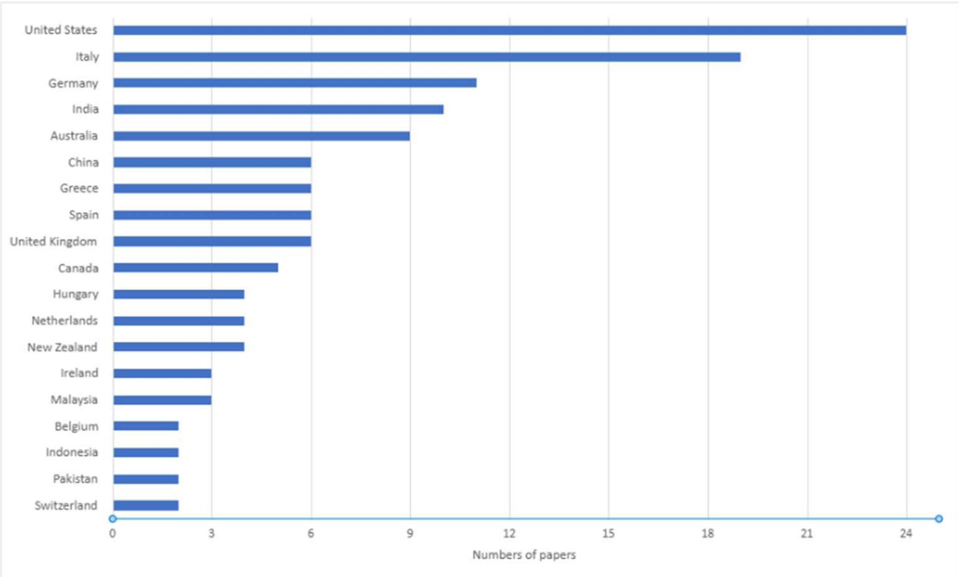


Figure 9 - Geographical distribution of studies related to the systemic dimension in agricultural technology adoption (Source: author's elaboration)

Most research on the adoption of agricultural technology was published in journal articles (79%), conference proceedings (15%) and books (6%) (Figure 10).

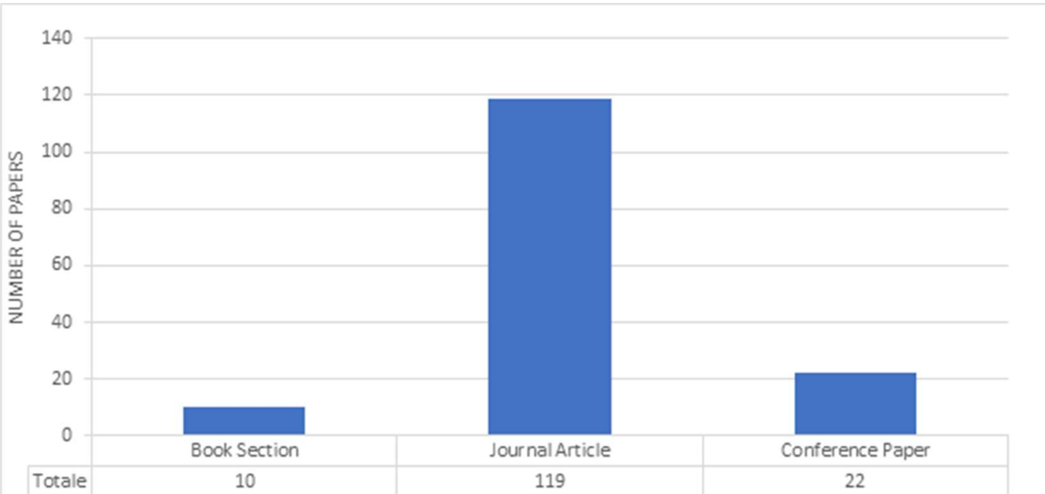


Figure 10 - Number of Papers per Type (Source: author's elaboration)

The journals with the highest number of articles are Precision Agriculture (23 %) and Smart Agricultural Technology (11 %). Other journals with significant contributions are Agricultural Systems, Sustainability (Switzerland), Agricultural and Food Economics and Technology in Society. All other journals made a negligible contribution. (Figure 11)

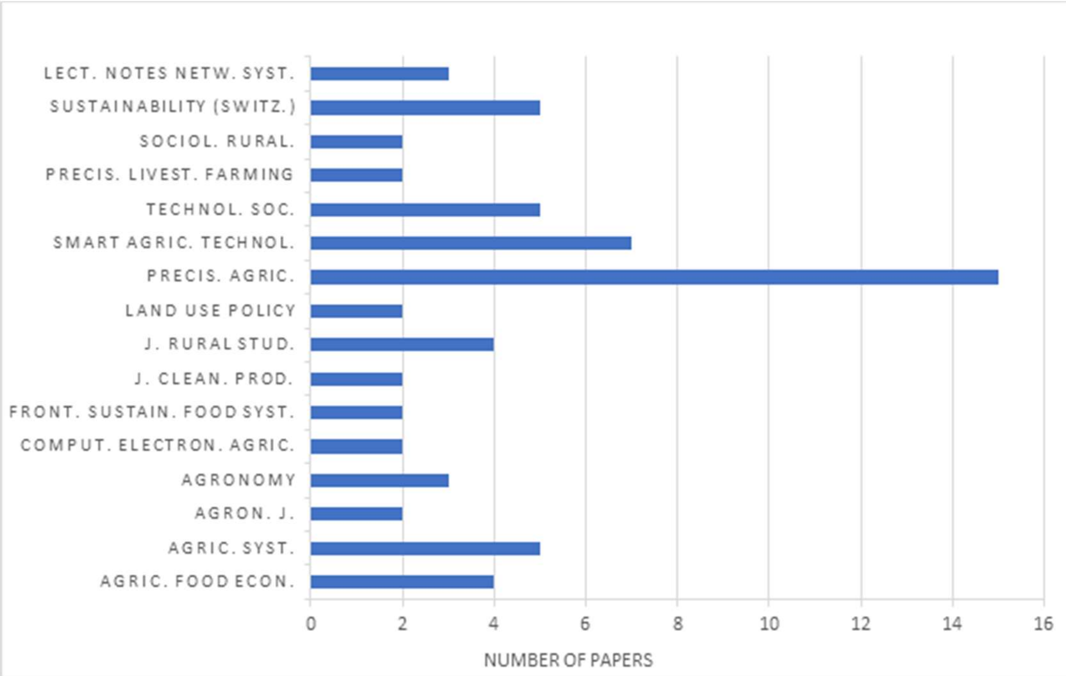


Figure 11 - Number of Papers per Journal. (Source: author's elaboration)

Network analysis

The aim of network analysis was to explore and visualize the underlying structure of relationships in literature. By applying network analysis techniques, the aim was to identify patterns, clusters and key units that are central to the area under investigation.

As shown in Figure 12, the coincidence network map consists of nodes (terms), which represent important concepts discussed in the selected articles, and edges (links), which indicate the strength of the relationship between the terms based on the frequency of their co-occurrence.

The size of the nodes reflects the frequency of a term: larger nodes correspond to more frequently mentioned concepts, and the color of the nodes groups terms into thematic clusters that indicate closely related research topics. Finally, the distance between two nodes indicates their correlation. The co-occurrence map was created by including terms that appeared more than five times in the title, abstract and keywords of the selected articles.

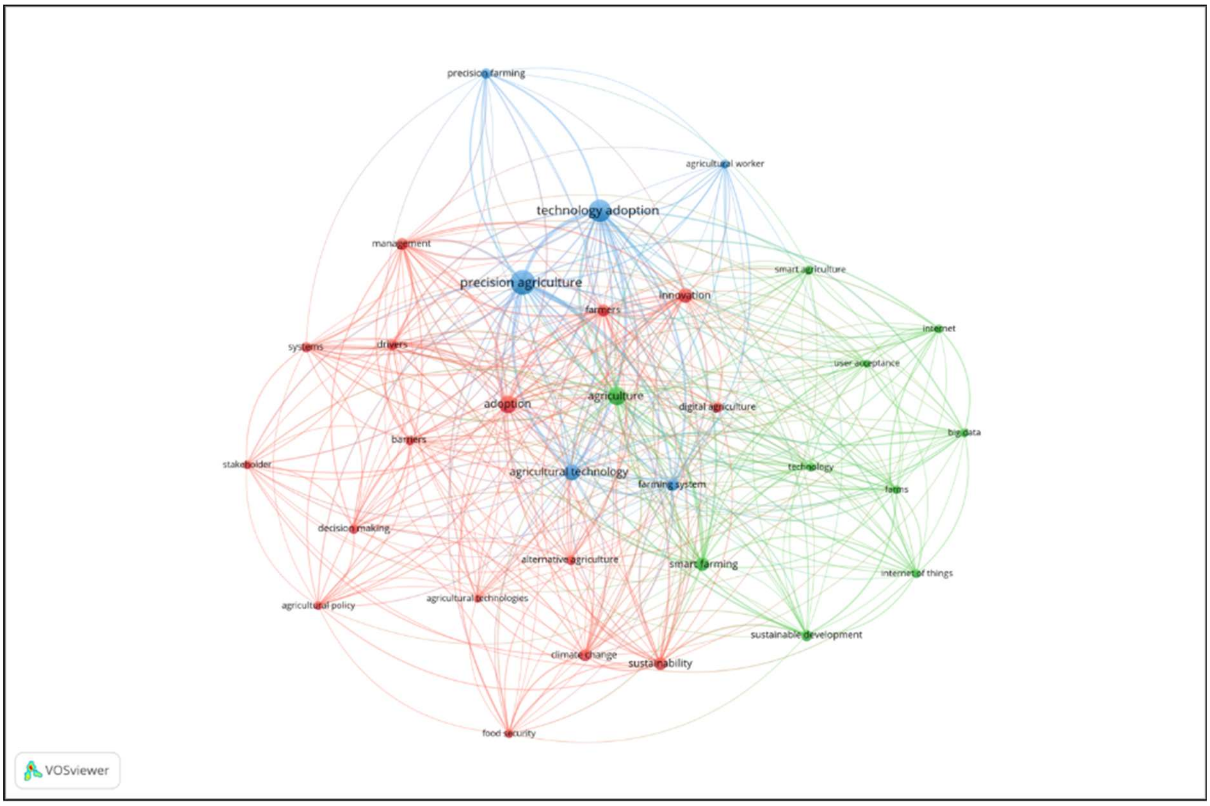


Figure 12 - Keyword co-occurrences map. (Source: author's elaboration)

The analysis reveals a complex and structured research landscape on technology adoption in agriculture. The key concepts that emerge most frequently include "precision agriculture" (with 55 occurrences), "technology adoption" (with 46 occurrences), “agriculture” (with 31 occurrences), “adoption” (with 29 occurrences), "agricultural technology," (with 24 occurrences), “innovation” (with 20 occurrences), and “smart farming” (with 18 occurrences), highlighting the growing interest and relevance of technology innovation within agricultural systems.

Furthermore, the keywords with the most and stronger interconnected links were "precision agriculture" (total link strength 208), "technology adoption" (total link strength 185), “adoption” (total link strength 122), "agricultural technology," (total link strength 121) “agriculture” (total link strength 118), “innovation” (total link strength 100), and “farming system” (total link strength 89) and “management” (total link strength 88).

Notably, the term "farmers", even scoring less frequency and connection, appears in a central position, emphasizing the crucial role that farmers play in adopting new technologies.

The overview of keyword co-occurrence mapped clearly highlights the centrality of the technological dimension within the adoption process. However, a general underestimation of the systemic component is outlined. Indeed, terms that refer to the systemic domain, such as “systems,” “stakeholders,” and “agricultural policy” are positioned at the edges of the map, pointing out a gap in the literature.

As can be seen in Figure 12, three clusters were formed, each represented by a specific color.

The first cluster comprised 6 elements, the second cluster was the largest with 13 elements, and the third comprised 10 elements.

The first cluster, highlighted in blue, is concerned with precision agriculture and the processes of technology adoption, in particular agricultural systems and agricultural labor with regard to the integration of new technologies into agricultural production systems. In this context, there is a close link between "precision farming" and "technology adoption," suggesting that research in this area primarily investigates the factors facilitating the adoption of precision technologies.

The second area, highlighted in red, concerns the system elements of the process of introducing agricultural technology. It looks at the barriers and drivers to technology adoption, as well as the broader implications for sustainability and climate change. Key terms such as "stakeholder," "agricultural policy," "decision making," "drivers," "barriers," "sustainability," and "climate change" indicate a strong interest in the socio-economic and environmental aspects influencing the dissemination of innovation in the agricultural sector. The presence of "agricultural policy" and "decision making" specifically suggests that public policies and business strategies play a key role in shaping technology adoption decisions. Moreover, the outer position of the words “stakeholders” and “system” highlights a lack of valuation of the role of systemic factors within the literature.

In addition, the weak connection between "sustainability", "climate change" and “adoption” highlights the need to align technological advancements with ecological and resilience-oriented goals.

The third, green-colored cluster deals with new technologies and digitalization and contains terms such as "smart agriculture," "big data," "Internet of Things (IoT)," "technology," and "user acceptance." This set of concepts fully identifies the technological dimension of the adoption process, reflecting the increasing research focus on connected and advanced digital tools enhancing farming efficiency. The strong presence of "big data" and "IoT" suggests that digital technologies are becoming fundamental in transforming traditional agricultural practices, making them more precise and data driven. Notably, the presence of "user acceptance" in the third cluster highlights the importance of behavioral factors in the adoption of agricultural technologies. However, "user acceptance" is weakly or not at all connected to system-related elements such as "system", "stakeholders" and “decision making” suggesting that research in this area primarily explores interactions of farmers with digital innovations, focusing on usability, perceived benefits, and technological integration rather than governance or policy-driven adoption strategies. The positioning of the term and its distant associations may suggest that more research is needed on farmer engagement in technology development process co-creation initiatives to encourage adoption and wider diffusion.

Figure 13 illustrates the evolution over time of key research topics in the area of agricultural technology adoption, highlighting shifts in focus over recent years. The color gradient, which ranges from purple (older) to yellow (newer), shows how different topics have gained or lost importance over time.

Originally, until 2021, research focused mainly on technology adoption in precision agriculture, with an emphasis on the management dimension of the technological process and little attention paid to system aspects, such as “stakeholder”, “system” and "agricultural policy", suggesting that the early studies focused on the institutional and policy framework that shapes agricultural innovation.

Strating from 2022, particular attention to the decision-making process faced by farmers has emerged. Keywords such as "barriers", "drivers", “decision making”, “user acceptance” and "farmers" were central during this period, reflecting a shift from technology to factors influencing the integration of new technologies into farming practices.

As the research progressed to 2022, the focus shifted to the digital transformation in agriculture, with increased attention being paid to the following aspects "big data", "alternative agriculture", and "smart farming". This phase shows a growing interest in the practical applications of digital tools and automation in agricultural systems.

By 2023, the research landscape will have evolved further, with a focus on connectivity and the role of digital solutions in modern agriculture. Keywords such as "digital agriculture", "Internet of Things" (IoT) and "Internet" are among the latest trends that point to a clear shift towards data-driven decision-making processes and the use of advanced digital infrastructures. At the same time, terms such as "sustainable development", "climate change", "sustainability" and “food security” indicate that technological innovations are increasingly being viewed in terms of long-term environmental and economic viability.

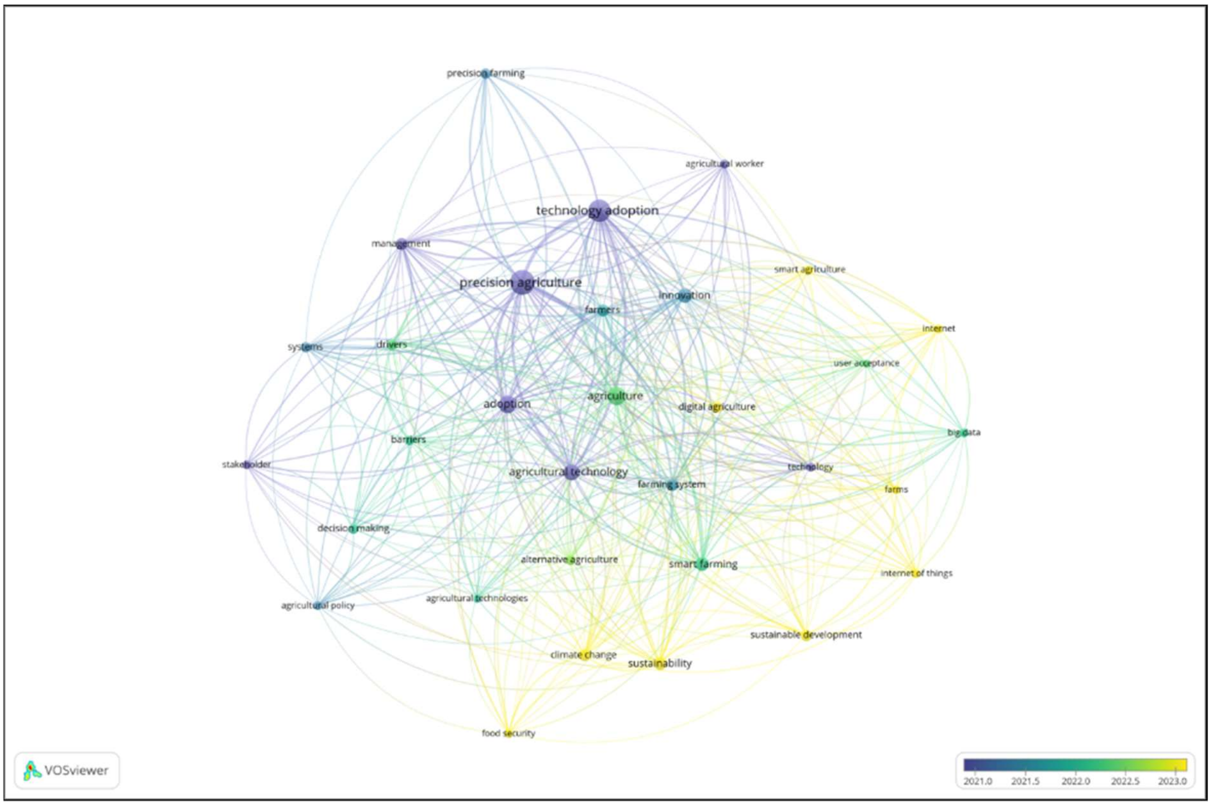


Figure 13 - Keyword co-occurrences map per year. (Source: author's elaboration)

The density map in Figure 14 provides a visual representation of the concentration and relevance of the most important research topics for the introduction of agricultural technology. The color intensity indicates the frequency of occurrence of terms, with yellow areas representing the most frequently discussed topics, while green and blue areas correspond to less frequently occurring terms.

The most conspicuous clusters are "technology adoption", "precision agriculture", and "adoption", which appear in the brightest yellow areas. This shows that these topics are at the center of the research landscape and underlines the importance of a meaningful understanding of the process of agricultural technology adoption.

In contrast, terms such as "user acceptance", "big data", "internet" and "internet of things" are found in less dense areas. This indicates that although these topics are part of the research landscape, they have not yet achieved the same status as core topics such as adoption and precision agriculture, which is consistent with the previous analysis of temporal development. Their positioning on the periphery is indicative of emerging trends, particularly in relation to digital transformation and connectivity in agriculture.

In addition, environmental and sustainability-related terms such as "climate change", "sustainability" and "sustainable development" are present, but in lower density. This suggests that the link between technology adoption and sustainability, while recognized, has not been as thoroughly explored as the more immediate concerns of adoption and precision agriculture.

Overall, the density map shows a strong focus on challenges and opportunities related to technology adoption, while also showing a growing interest in digitalization and sustainability. The lower density of terms related to user adoption and connectivity indicates potential research gaps and highlights the need for further study on how farmers are using and integrating these technologies into their practice.

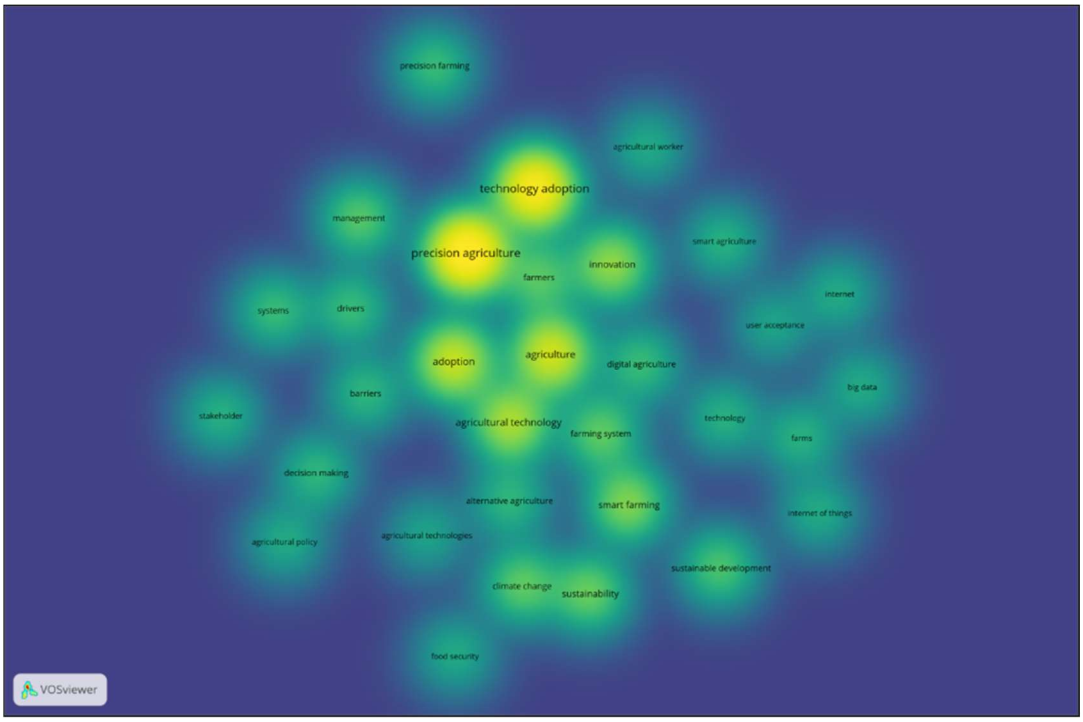


Figure 14 - Density map keyword co-occurrences (Source: author's elaboration)

Co-authorship analysis is an advanced method of bibliometric network analysis that aims to form social groups in order to investigate and analyze extensive collaboration. The analysis was carried out using VoSviewer software, which enables the identification of author partnerships in a research field. In total, 622 authors from 151 selected publications over a ten-year period contributed to the study of the systemic dimension in the process of technology adoption (Table 10).

Table 10 - Distribution of the number of publications among authors

Documents	Authors number	Proportions
1	581	93.4%
2	33	5.3%
3	4	0.6%
4	2	0.3%
5	1	0.2%
6	1	0.2%
Total	**622**	**100.0%**

The VOSviewer representation consists of nodes representing authors and links indicating relationships, e.g. collaboration between authors. The strength of these relationships is quantified by the Total Link Strength (TLS), which reflects the cumulative weight of an author's connections with other authors in the network. A higher TLS value indicates stronger collaboration within the network. The degree of collaboration between authors varies from 0 to a maximum of 40 links, with most authors at the lower end of the scale (Table 11).

Table 11 - Distribution of the Total Link Strength among authors

TLS	Authors	Proportions (%)
0	6	1.0%
1	38	6.1%
2	109	17.5%
3	94	15.1%
4	60	9.6%
5	54	8.7%
6	82	13.2%
7	42	6.8%
8	56	9.0%
9	5	0.8%
10	32	5.1%

12	2	0.3%
13	12	1.9%
15	1	0.2%
16	16	2.6%
18	8	1.3%
25	2	0.3%
17	2	0.3%
44	1	0.2%
Total	**622**	**100.0%**

As part of the mapping process, thresholds can be set for the number of documents to be included in the analysis in order to ensure the relevance and interpretability of the visualisations. In this case, no minimum threshold was applied due to the distribution of publications, and therefore a threshold of at least one document was retained. The analysis was nevertheless limited to authors with a higher number of connections (more than 10), resulting in 76 authors who together accounted for almost 12% of the total.

Figure 15 illustrates the overall collaboration network between authors in the systemic area of agricultural technology adoption. The map, organised into different colours, identifies eight interconnected clusters with 409 connections, corresponding to a total connection strength of 479. Clusters are useful for highlighting groups of authors and their academic relationships. In this collaboration framework, most clusters remain relatively isolated, with the exception of the purple cluster, which contains the most influential author in the field, Fountas Spyros, acting as a link between the red and green clusters.

The size of the nodes reflects the number of publications of each author, allowing the identification of the most influential contributors. Among the most prominent authors are Fountas, S.; Vecchio, Y.; Eastwood, C.; Masi, M.; Adinolfi, F.; De Rosa, G.; Gemtou, M.; and Gómez-Barbero, M.

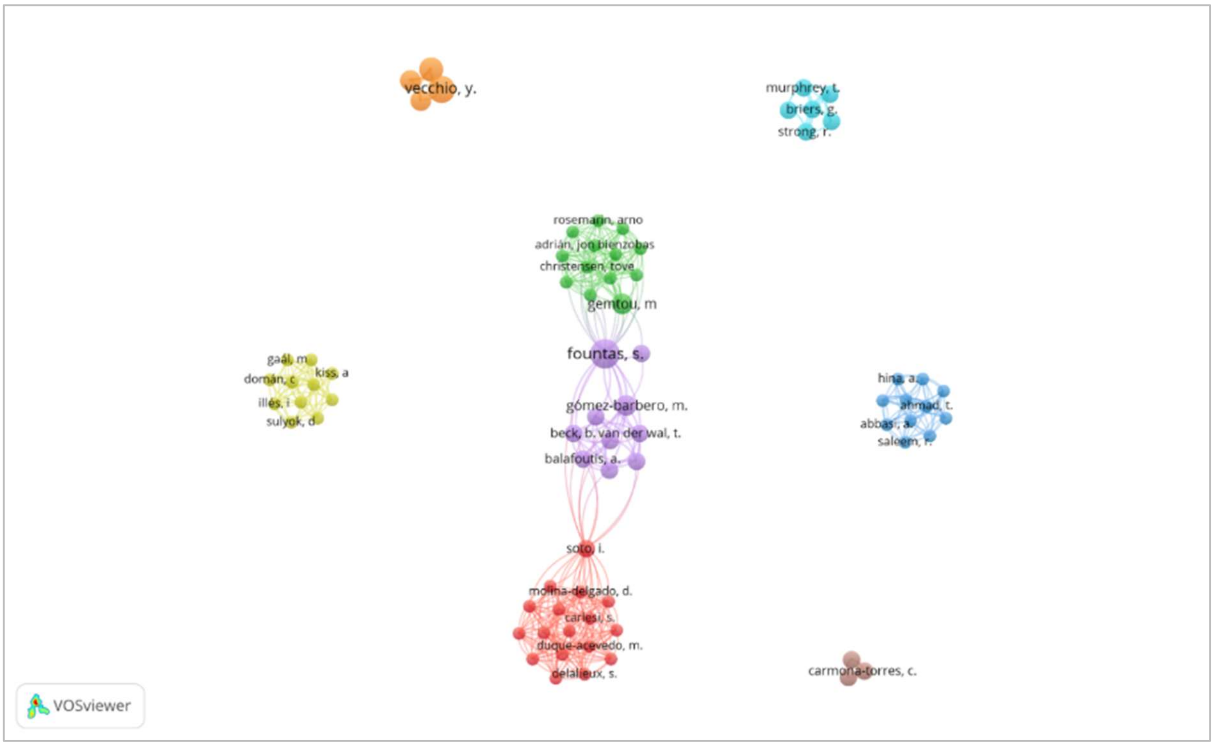


Figure 15 - Co-authorship network map (Source: author's elaboration)

The results show that most authors have not yet established fruitful collaborations outside their research groups. However, two prominent authors have made efforts to expand their social networks. For example, Fountas S. has 23 connections, 14 of which are to external clusters, and Soto I. has 25 connections, 9 of which are to external clusters.

Thematic analysis

Empirical studies accounted for about 60% of the selected documents, together with 6.1% books, 28.8% reviews, and finally 6.8% that were not identified because there was no complete access to the document.

Research methodology. The empirical studies predominantly used quantitative methods (53.2%), followed by qualitative (23.4%) and mixed methods (14.3%). Only a few studies dealt specifically with case studies (7.8%) and co-design approaches (1.3%). Quantitative studies were mostly based on surveys, while qualitative research included several methods, mainly individual interviews, focus groups, and the Delphi method.

Regarding the theories and models that served as the basis for the empirical studies, the most striking feature is the absence of reference theories in almost 80% of the documents analysed. Among the theories used, the mixed approach was the most frequently adopted, while single theories such as AKIS – Agricultural Knowledge and Innovation System, DOI – Diffusion of Innovations, and TPB – Theory of Planned Behaviour (2.27%), TAM – Technology

Acceptance Model, UTAUT – Unified Theory of Acceptance and Use of Technology, and ADOPT – Adoption and Diffusion Outcome Prediction Tool (7.41%) were the only ones explicitly mentioned. It is noteworthy that most of the studies without theoretical references originated from quantitative methodology.

With regard to the type of research participants, only 3.9% of the empirical studies did not provide any information or could not be verified due to lack of access to the full document. Farmers were the most represented group (54.55%), followed by other individual categories such as cooperatives, researchers, and students, which were only marginally represented. Conversely, studies involving multiple stakeholders accounted for 33.77%.

The integration of digital technologies on farms is influenced by many factors, including the agricultural and technological context of reference. About 60% of the empirical studies analysed did not refer to a specific agricultural system. Among those that did, arable farming was the most represented (62.5%), followed by livestock farming (18.75%) and fruit growing (15.63%). Organic and agroecological farming were addressed in only 3.13% of cases, while hydroponics and vertical farming were completely absent, with the exception of overview documents.

Regarding the type of technology examined, about half of the papers referred to the general technological landscape, such as smart farming or digital agriculture. In contrast, the most frequently examined technologies were precision farming and climate-smart agriculture (15.25%), Internet of Things (10.7%), blockchain, unmanned aerial vehicles (UAV), and decision support systems (8.47%).

Content analysis

Content analysis was conducted on the most relevant articles identified through the data extraction form in order to investigate how the systemic dimension in the adoption of agricultural technologies has been defined and developed in the literature.

Of the 28 articles selected, 4 were not accessible for a full read and were therefore excluded from the analysis. In addition, studies focusing on China were included, as the country plays a dominant role in the global supply chain and is considered the largest manufacturing economy in the world (Rauniyar et al., 2024).

The results are presented below according to the research questions.

Research question 1. What types of research design and methodologies have been employed?

Half of the contributions used a qualitative research methodology, with interviews being the most common instrument, followed by workshops, the Delphi method and, in only one case, social media contributions. Participatory methods were almost completely absent, with the exception of a single case in which a co-design workshop with stakeholders was conducted. Quantitative methods accounted for one quarter of the studies, while mixed methods represented 20%, with surveys and interviews often combined.

In terms of theoretical frameworks, the majority of studies were not based on any theory (65%). Among those that relied on theories, a proportion adopted a mixed framework (12.5%), while Roger's Diffusion of Innovation theory was the most frequently applied, both as a single framework (8.3%) and within mixed approaches. Other theories used include Ontological Security, Malerba's Innovation System theory, and the Adoption and Diffusion Outcome Prediction Tool (ADOPT).

Regarding research participants, most studies (70%) involved multiple categories, such as farmers, advisors, technology providers, researchers, cooperatives, and policy makers. Among individual categories, experts were the most common (12.5%), followed by farmers, extension professionals, and web users (each 4.2%).

With respect to the technology context, most studies (66%) referred to digital technologies in general. Specific technologies analysed included Artificial Intelligence (AI), laser-based autonomous weed control, blockchain, climate-smart agriculture (CSA), and the Internet of Things (IoT). In two cases, reference was made to precision agriculture and other innovations that can be attributed to the broader category of digital technologies.

As for the agricultural systems investigated, most studies (37.5%) did not specify a particular system. Among those that did, arable farming was the most studied (25%), followed by livestock and fruit growing (8.3% each) and viticulture (4.2%). Mixed systems were also considered, including arable and fruit growing (8.3%), livestock and arable (4.2%), and organic/agroecological farming (4.2%).

Geographically, Europe accounted for 62.5% of the studies, with Germany being the most represented country (16.7%). Other important areas were Australia and New Zealand (12.5%), the USA (8.3%), and Canada and China (4.3%). Global-level studies represented 8.3% of the total.

Research question 2. How has the systemic dimension in agricultural technology adoption been defined?

This section examines how the systemic dimension of agricultural technology adoption has been defined, comparing the findings with the definition provided in the introduction, and providing an overview of the main levels of analysis and systemic adoption factors.

The systemic dimension is characterised by the relationships that generate and disseminate knowledge, promote adoption and diffusion processes, and shape the overall dynamics of technological innovation. Its defining element is the interaction between different actors (peers, providers, advisors, cooperatives, institutions, and markets) and infrastructures that influence diffusion and integration, encompassing technical, economic, social, and regulatory aspects within a dynamic and networked perspective (Benyam et al., 2021; McGrath et al., 2023; Osrof et al., 2023; Sadjadi and Fernández, 2023).

A smaller proportion of the studies (8.3%) only partially aligned with this definition, as they focused primarily on the role of key actors in technology diffusion, such as agricultural advisory services, who play a crucial role in addressing farmers' uncertainty and supporting knowledge and decision-making processes in the adoption of smart farming technologies.

By contrast, one third of the studies (33.3%) did not adopt a systemic perspective, instead focusing on individual actors.

The determinants of adoption identified in the reviewed studies were grouped into meaningful categories linked to the relevant actors. As shown in Table 12, the 52 identified factors were relatively evenly distributed across categories, with social interactions (29%) and access to finance (21%) emerging as the most important. The full list of factors is provided in Addorisio et al. (2025b).

Table 12 - Factors distribution among categories (Source: our elaboration)

Categories of factors	Factors Proportion (%)
Access to funding or economic incentives	21%
Governance and coordination structures	17%
Institutional factors	15%
Social interactions	29%
Technical support and advisory services	17%
Total	**100%**

The category of social interactions refers to the relationships between end users of the technology and the actors who promote it, through which knowledge is disseminated, and the benefits of the technology are demonstrated. The factors most frequently mentioned in the studies included the dissemination of results, the provision of information, and social support. This category encompasses a wide range of actors and thus highlights the importance of the system's ability to create networks among stakeholders.

The category of access to finance and economic incentives reflects the economic component of the agricultural technology adoption process. Its prominence in the studies analysed confirms its central importance, with public financial instruments (e.g., EU agricultural policy) and private institutions (e.g., banks) playing a key role. The most frequently represented factors were financial support, flexible financing, financial incentives, and economic benefits and feasibility.

The category of technical support and advice concerns meso-level actors who play a crucial role in bridging the gap between technology and farmers, actively contributing to its dissemination. The factors most often cited were technical support, increased technical advice, and extension services, indicating a predominantly advisory rather than educational role.

Institutional factors represent the interaction between the public and economic dimensions of the adoption process. These are interpreted through the role of public institutions that support the sector via regulatory and incentive measures. The most relevant factors were policy measures, funding programmes, environmental incentives, and government regulations and compliance, with the environmental dimension increasingly framed as facilitating technology diffusion.

Governance and coordination structures refer to the organisational arrangements that facilitate or hinder the dissemination, validation, and integration of technologies into existing agricultural systems. Factors identified in the literature included the importance of cooperatives, coordination among actors, and transparent project management. These findings suggest that governance and coordination structures act as mediators of the system, managing normative, economic, and attitudinal dimensions, and thereby playing a central role in the integration of technologies at the local level.

Finally, it is worth noting that interactions among determinants were explicitly examined in only 12.5% of the reviewed studies. Nevertheless, these contributions illustrate the complexity of the relationships among factors and show that addressing one determinant can have cascading effects on others.

Research question 3. How has the systemic dimension been addressed and developed? What approaches have been taken?

The systemic dimension in the reviewed literature was developed through different approaches, each emphasising specific perspectives of the innovation adoption process, including methodological orientations, stakeholder perceptions, and the interactions between adoption determinants.

First, several studies (Busse et al., 2014; Kutter et al., 2011; Marshall et al., 2022) analysed the systemic dimension by examining stakeholder perceptions, with the aim of identifying differences between groups. This approach typically highlighted actors that could act as facilitators or barriers, enabling targeted interventions or improved collaboration within the innovation system.

Another group of studies, while still focusing on stakeholder perceptions, shifted the emphasis to the relationships among adoption factors. These studies stressed that factors are interrelated and need to be considered in combination. For example, (Pedersen et al., 2024) demonstrated that determinants influencing the adoption of climate-smart agriculture in Europe are interlinked, pointing to the importance of examining such interactions in order to promote behavioural change towards sustainable food systems along value chains.

A third perspective focused on categorising and characterising adoption determinants individually, with the aim of clarifying specific elements that influence behaviour in complex innovation environments. Unlike the relational approach, this perspective concentrated on discrete factors rather than their interconnections.

Finally, a fourth orientation explicitly involved co-creation and co-innovation processes, engaging farmers and stakeholders during the design of tools or solutions. In these cases, the innovation process was driven by stakeholder needs and experiences, allowing for the development of tailored and contextualised solutions.

Not all studies adopted a fully systemic perspective. Some limited their analysis to specific groups of actors, but remain relevant due to the strategic role of these actors as intermediaries between technologies and end users. For instance, (Mignani et al., 2024) examined innovation intermediaries (Italian operating groups), focusing on their role in driving adoption through interactive innovation models emphasising co-decision and co-design. Although systemic relationships were not comprehensively addressed, this perspective sheds light on governance mechanisms that facilitate technology diffusion among farmers and foresters.

Similarly, (Bryant and Higgins, 2021; Eastwood et al., 2019) analysed the role of meso-level actors such as agricultural extension agents and agronomists, who act as intermediaries in technology diffusion. Although these analyses did not adopt a fully systemic perspective, they offered important insights into how advisors' perceptions of uncertainty influence their ability to promote innovation, as well as into the evolving skills and roles of extension professionals in data-driven smart farming contexts.

Finally, (Padyab et al., 2020) examined the experiences of large-scale pilots (LSPs), focusing on adoption processes in specific case studies. By analysing end-user challenges and barriers from a process-oriented perspective, this study provided practical insights into real-world implementation contexts, even if it did not incorporate the full systemic integration of actors and factors.

3. Empirical studies

3.1. Barriers and Drivers of Digital Agriculture Adoption: Insights from Italian Farming Stakeholders

3.1.1. Introduction

Building on the evidence synthesised in the general literature review (Chapter 2.1) and the scoping review on the systemic domain (Chapter 2.2), this chapter addresses the adoption of digital technologies in Italian agriculture from a systemic, technology-neutral perspective, focusing on the perceptions of key stakeholders across the agri-food system.

The disruptive potential of digital technologies in agriculture makes it particularly important to understand the mechanisms of adoption and diffusion (Barbosa Júnior et al., 2024; Shang et al., 2021).

Prior research highlights that adoption is a multi-factor process in which individual capacities and technology attributes interact with systemic conditions - advisory services, governance arrangements, market structures, and opportunities for coordination and data sharing. (Dibbern et al., 2024; Fragomeli et al., 2024; Osrof et al., 2023; Verbeke et al., 2024).

In the Italian context, agricultural technology adoption is still at incomplete, with evidence pointing to significant mismatches between technological supply and actual farm demand (Politecnico di Milano, 2024). Many farms lack the necessary equipment and skills to collect and process data effectively, which hinders the integration of digital solutions.

Despite the extensive literature on innovation diffusion, there is still no convergence regarding the theories and models that can adequately explain technology adoption. Some authors underscore the specificity of theories in modelling adoption (Dissanayake et al., 2022; Osrof et al., 2023), while others question their general applicability across technologies and contexts (Montes De Oca Munguia and Llewellyn, 2020).

Although several classifications of adoption determinants have been proposed (Dibbern et al., 2024; Fragomeli et al., 2024; Kakkavou et al., 2024), most studies remain focused on the farm level. Recent research instead emphasise the importance of considering both farm-level and systemic factors (Gemtou et al., 2024; Shang et al., 2021), calling for a more holistic perspective, recognising the importance of stakeholder engagement, co-design initiatives, and interactive innovation models (Knierim et al., 2019; McGrath et al., 2023; Monteiro Moretti et al., 2023; Vecchio et al., 2022b).

These contributions underline that farmers' ability to adopt digital solutions is shaped not only by individual characteristics and technology attributes, but also by systemic factors such as advisory services, governance structures, and opportunities for collaboration across the value chain.

At the same time, the reviews in Chapter 2 identified three persistent gaps: (i) divergence and fragmentation among explanatory factors, (ii) limited assessment of how system interactions shape individual behaviour, and (iii) insufficient attention to stakeholders' perceptions in digital farming contexts. These findings show that systemic determinants are repeatedly acknowledged but often under-specified, weakly operationalised, and inconsistently theorised across empirical studies. To strengthen interpretability, this chapter therefore links inductively derived themes to four recurring systemic domains discussed in the literature— advisory and technical support structures, governance and coordination arrangements, market arrangements, and data infrastructures—treating them as an interpretive map rather than as a coding framework.

In response to these gaps, this chapter presents an exploratory qualitative study that investigates stakeholders' needs and demands for digital technologies, alongside the barriers and enablers that influence diffusion within the Italian farming system. Particular attention is given to the role of systemic interactions and multi-actor coordination in shaping adoption pathways. The qualitative analysis is exploratory and follows an inductive logic: themes and categories are generated bottom-up from the transcripts through latent content analysis. The evidence from literature reviews is then used at the interpretation stage as an analytical lens to relate the emergent findings to recurring systemic domains discussed in the literature, without constraining category generation.

The contribution of this chapter is twofold. First, it translates the conceptual insights from the literature (Chapters 2.1 - 2.2) into empirically grounded accounts of barriers, drivers, and needs observed by actors directly engaged in innovation processes. Second, it provides practice-oriented indications on governance, advisory, and multi-actor coordination, that will inform the operationalisation of systemic constructs and the subsequent quantitative modelling in Chapter 4.

3.1.2. Methodology

In this study, an explorative approach was used to investigate the phenomenon. Consistent with an inductive logic, the analysis proceeds from participants' accounts to generate categories and higher-order themes through a process of abstraction. Latent content analysis is used to derive meaning units and categories bottom-up from the transcripts. The literature review is subsequently mobilised to support interpretation and to situate the emergent findings within the broader debate on systemic determinants of digital agriculture adoption, without imposing a priori categories..

The investigation was based on two alternative and complementary qualitative research methods, focus groups and interviews, that have been previously used to investigate stakeholders' decision-making process in the agri-food sector (Galabuzi et al., 2021; Marcu et al., 2015; Osei et al., 2021; Sabbagh and Gutierrez, 2023).

Alternative designs (e.g., a single-method interview study or a convergent parallel design) were considered less suitable because the study aimed not only to elicit individual experiences but also to observe cross-actor negotiation and shared meanings around data, coordination, and governance constraints. Focus groups were therefore used first to surface collective framings and interdependencies among actors, while semi-structured interviews were used subsequently to deepen emerging themes, capture role-specific nuances, and triangulate findings. This sequence supports construct refinement and the later operationalisation of systemic mechanisms in the farmer survey.

Two Focus Groups (FGs) were organised to discuss stakeholders' demands and barriers regarding the use of tools for tracing farming activities at field level. At the same time, in-depth interviews were conducted to further investigate these demands and barriers from the perspective of key informants.

A FG is defined as a discussion conducted by a moderator in a non-structured and natural manner with a small group of participants (Malhotra et al., 2013). This method was chosen as a suitable tool for gathering qualitative information to address specific research questions (Bloor et al., 2001), capturing opinions, motivations, decisions, and priorities on the topic of interest.

In-depth interviews consist of interactive conversations in which a researcher poses questions and the participant responds (Knott et al., 2022). In this study, semi-structured interviews were conducted, guided by a topic outline derived from the outcomes of the focus groups. This combined approach allowed for extended discussions and more nuanced insights (Monteiro Moretti et al., 2023; Osei et al., 2021).

Table 13 summarises the categories of respondents and the number of participants in each method. The two FGs involved a total of 14 participants, ranging from farmers' associations to farm entrepreneurs and machinery and service providers. Participants were selected to cover different interest groups, including both public and private stakeholders. One FG took place in February 2023 in Bologna (Emilia-Romagna Region, Italy) with 6 participants, and another in September 2023 in Catania (Sicily Region, Italy) with 8 participants.

In addition, 14 semi-structured interviews were carried out with a broader set of stakeholders along the food supply chain, focusing on their needs regarding digital technology adoption and the heterogeneity of related barriers. Interviewees included farmers, machinery, service and technology providers, representatives of cooperatives, certification bodies, and policy makers.

The selection of participants was based on a purposive sampling strategy, generally considered appropriate for interview-based research when the number of respondents is too small to aim for statistical representativeness (Knott et al., 2022). The number of interviews was defined according to the principle of saturation (Knott et al., 2022), resulting in a total of 27 key informants recruited from the Italian farming supply chain, which represents a critical component of the national agricultural sector.

Table 13 - Summary of the interviewees' characteristics

	Focus Groups	Interviews
Farmers	5	1
Machinery providers	2	1
Input providers	1	
Associations	3	
Service and tech providers	2	3
Consultants		4
Processors		1
Certifiers		2
Policy makers		2
TOTAL	**13**	**14**

SOURCE: authors' elaboration

Participants were selected according to two main inclusion criteria: (i) playing a relevant role within the supply chain and (ii) demonstrating an interest in the innovation system under investigation.

The focus group discussions centred on: i) data needs of each actor along the supply chain; ii) main barriers to digital technology adoption; and iii) expected benefits from adoption.

Semi-structured interviews addressed general perceptions of digital farming technologies, barriers and drivers of adoption, and stakeholders' needs in managing field activities, through a set of seven open-ended questions.

In both FGs and interviews, participants were informed about the study objectives.

Data collection took place between February and October 2023. Focus groups lasted approximately 1 hour and 30 minutes, while interviews lasted about 1 hour each.

The collected material (transcripts of FGs and interviews) was analysed through latent content analysis, a systematic and objective method for generating inferences from verbal, visual, and written data (Downe-Wamboldt, 1992).

The analytical process, adapted from Bengtsson (2016), involved the following stages:

1. Decontextualisation – classification of participants' statements into units of meaning.
2. Recontextualisation – grouping of statements into broader sense units, excluding information irrelevant to the research questions.
3. Categorisation – organisation of meaning units into homogeneous categories, derived from the data and aligned with the research questions.
4. Data reduction – elimination of redundancies and synthesis of the material into four overarching categories.
5. Data interpretation – elaboration of general explanations of the phenomenon under study.
6. Classification – identification of interpretation classes to enhance the objectivity, comparability, and robustness of the results.

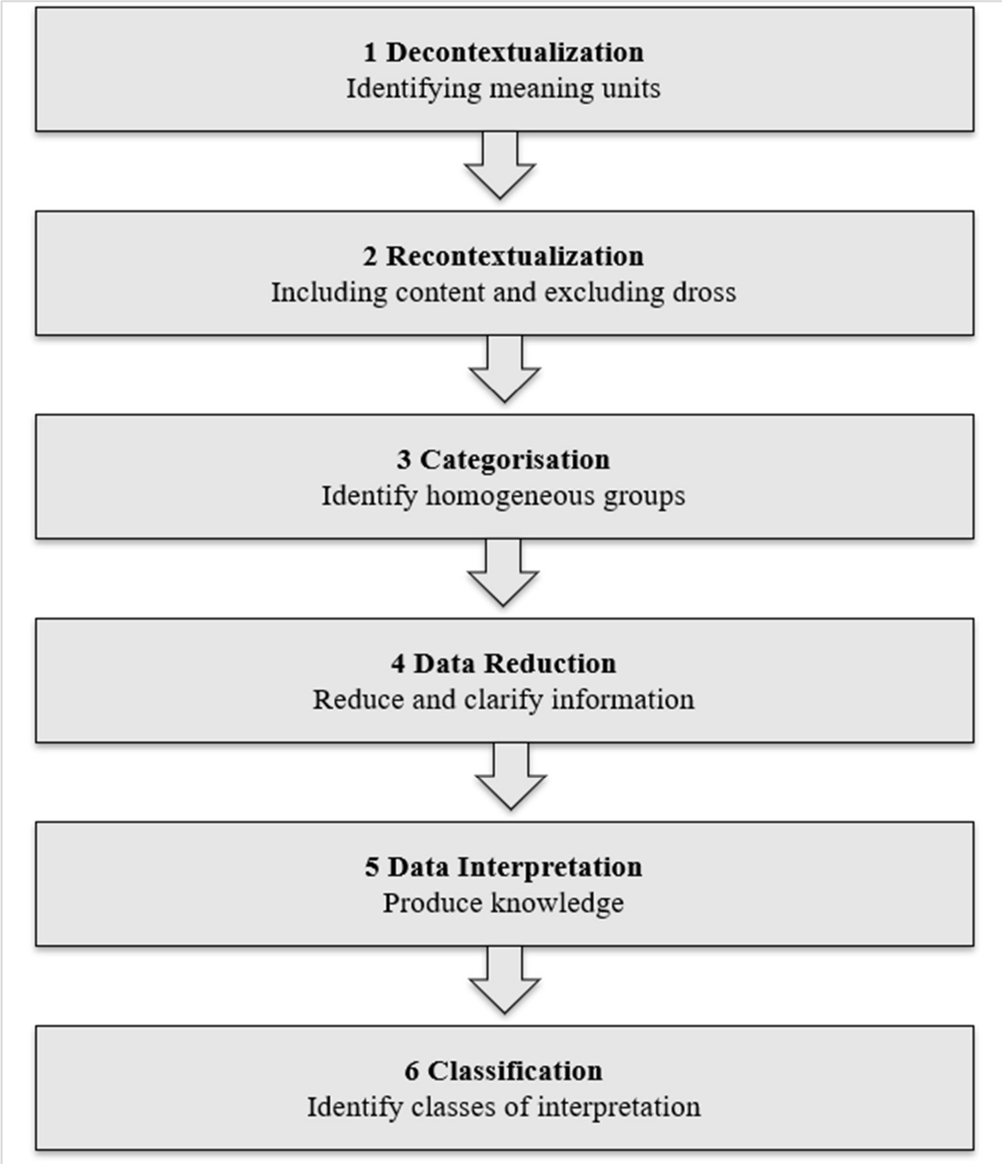


Figure 16 - Overview of data analysis process (adapted from Bengtsson (2016))

To strengthen interpretability, the inductively derived themes are related to four recurring systemic domains discussed in the literature—treated here as an interpretive map (not a coding framework). Advisory and technical support structures refer to the knowledge-and-support ecosystem that enables adoption through training, advisory/extension, intermediaries, and the connections among organisations and actors that circulate know-how and reduce uncertainty (often framed within AKIS, i.e., networks of organisations/people, their interactions, and the institutional infrastructure that supports them). Governance and coordination arrangements denote the institutional and collective set-up that shapes how actors align incentives and responsibilities—through policies, rules, and coordination mechanisms that can enable diffusion (e.g., via incentives/subsidies, institutional support, and regulatory safeguards that reduce risk and foster uptake). Market arrangements capture the market and value-chain conditions that influence adoption opportunities, including “market readiness” (the extent to which local markets provide the infrastructure, availability, and support necessary for implementation) and “market dynamism” (competitive pressure and market change that motivate investment and upgrading). Data infrastructures concern the technical and organisational conditions for data to be generated, integrated, and used, including interoperability and data-related governance (ownership, access rights, transparency of contractual terms, security/privacy, and power asymmetries that affect farmers’ capacity to benefit from data sharing) (McGrath et al., 2023; Osrof et al., 2023; Shang et al., 2021).

3.1.3. Results

Results are presented by reporting the derived themes and units of sense that emerged from the latent content analysis. In the discussion, these findings are related back to the systemic issues emphasised in the literature review to strengthen interpretability and to support the link with the subsequent empirical phases.

Data analysis, summarised in Table 14, identified three major themes: (i) data requirements for improving the management of farming activities, (ii) determinants of the innovation adoption process, and (iii) benefits related to the adoption of digital technologies.

Each theme was further articulated into specific units of sense, which can be interpreted as opportunities, challenges, or actions concerning the adoption and diffusion of digital agriculture.

Table 14 - Summary of categories

CATEGORIES	UNITS OF SENSE	
Data requirements	1	Data availability
	2	Demands
	3	Data management
	4	Data security and property
Adoption determinants	5	Adoption drivers
	6	Adoption barriers

Adoption benefits	7	Economics benefits
	8	Environmental benefits
	9	Social benefits
	10	Relations with supply chain

Data requirements

This category encompasses four units of sense: data availability, demands, data management, and data security and property.

Regarding data availability and demands, participants acknowledged that farm data are generally sufficient for current management needs, although opportunities for further improvement exist. The main limitation was not the absence of data but the underutilisation of their potential, due to both limited technological skills and a lack of awareness about their usefulness.

Interviewees identified seven additional requests for data collection and monitoring, including: soil mapping; predictive data for crop protection, nutrition, and water management; input savings and yield monitoring to evaluate farm efficiency; predictive maintenance of machinery (reported by one participant); traceability of farming activities for public reporting; and carbon credits evaluation as an indicator of environmental performance (reported by one participant).

With respect to data management, the emphasis was placed on the challenges of handling and processing data, rather than on their collection. Stakeholders highlighted the importance of Decision Support Systems (DSS) to address priority needs, stressing that integration of data from multiple sources (e.g., sensors, remote sensing, field observations) and interoperability across platforms remain critical bottlenecks.

The complexity of managing digital tools reinforced the perceived need for technical support and training programmes. Furthermore, stakeholders expressed concerns about the effectiveness of national public incentives, noting that linking subsidies for conventional equipment to the purchase of digital technologies may foster "unfunctional adoption", aggravating farmers' constraints and limiting meaningful integration into existing practices.

Finally, data security and ownership were discussed in terms of perceived risks of manipulation and the protection of digital rights and intellectual property. Overall, participants reported a relatively low perception of risk and considered data sharing as an opportunity to improve farm operability. While ownership of data was firmly claimed, confidence in service and technology providers was generally high.

Innovation adoption process

The adoption process emerged as the most prominent theme, attracting strong attention across all participants. It refers to the determinants that either hinder or facilitate adoption and diffusion. The main barriers and drivers are reported in Table 15.

Barriers most frequently highlighted included: limited attitude and trust toward innovations; cultural resistance linked to traditional habits and beliefs; lack of awareness of benefits and usefulness; farm size and production systems that restrict investment capacity given the high costs of technologies; insufficient technical support for data interpretation; lack of expertise across the supply chain; and unfavourable biophysical conditions linked to farm location.

In contrast, drivers were associated with the potential of digital technologies to improve economic performance, primarily through reduced operational costs. Some participants also underlined the importance of environmental benefits, particularly in resource-constrained contexts. Interactions among actors through aggregation, information exchange, and trust building, were identified as crucial mechanisms to strengthen competitiveness and accelerate diffusion. Finally, political and societal pressure to ensure compliance, together with market demand for reliable products, emerged as additional enabling factors.

Table 15 - Determinants of digital agriculture adoption according to Italian stakeholders interviewed (full list).

BARRIERS	DRIVERS
Lack of attitude and trust toward innovations	Contractors’ availability
Cultural barriers	Technical support
Lack of awareness of technology benefits and usefulness	Training
Lack of information availability	Availability of information on technology
Lack of extension service availability	Laws and regulations
Farm succession (turnover)	Political and societal pressure
Farm size	Economic performance improvement
Farm location/region (bio-physical conditions)	Environmental performance improvement
Risk management attitude	Interactions to increase knowledge, confidence and competitiveness

Type of cropping system Education level Lack of technology competence at different levels Barrier from farm subsidies Farm system (specialization and crops profitability) Low investment capacity Lack of technical support	

Adoption benefits

Reported benefits reflected the triple bottom line (economic, environmental, and social dimensions) framework (Norman and MacDonald, 2004) and the role of digital technologies in strengthening relationships across the supply chain.

Economic advantages were the most frequently cited, particularly in terms of operational cost reduction. Nevertheless, strategic and long-term economic planning was largely absent, with technologies often applied in a stand-alone manner rather than embedded in broader data-driven management systems.

Social benefits, such as improved safety and working conditions, were less frequently mentioned and mainly associated with reduced risks and enhanced organisational capacity.

Environmental benefits were recognised, but often framed in connection with economic efficiency, especially in relation to soil fertility and climate risk management.

A final dimension concerned supply chain relations, where digital tools were perceived as enabling stronger aggregation initiatives. These fostered risk-sharing, improved competitiveness, and increased farms' capacity to invest and innovate. Participants also valued the role of digital technologies in enhancing compliance and traceability, thus improving reliability within specific supply chains.

3.2. What factors affect the Italian farmers' intention to adopt digital technologies?

3.2.1. Introduction

The adoption of new technologies in agriculture is a complex and dynamic process shaped by multiple interacting factors. While the literature has extensively examined the mechanisms of innovation diffusion, there is still no consensus on a single theoretical or modelling approach that can comprehensively explain the phenomenon.

Existing studies have applied diverse theories, ranging from marketing, sociology, economics, and psychology, each focusing on specific aspects of the adoption process and often developed for different innovation contexts (Dissanayake et al., 2022; Montes De Oca Munguia et al., 2021; Osrof et al., 2023).

Some authors argue for the specificity of theories in modelling distinct dimensions of adoption, while others question their generalisability across technologies and practices (Montes De Oca Munguia et al., 2021). For example, Osrof et al (2023) identified 24 distinct theories employed to explain the adoption of smart farming technologies, with prominent approaches including the Technology Acceptance Model (TAM), Diffusion of Innovation (DOI), Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2), Theory of Planned Behaviour (TPB), Technology-Organisation-Environment (TOE) framework, and Random Utility Maximisation models.

However, despite their wide application, the analytical methods, selection of explanatory variables, and degree of conceptual integration remain heterogeneous (Montes De Oca Munguia and Llewellyn, 2020).

From a modelling perspective, the literature reveals important differences in the way adoption is conceptualised, whether from an individual or population perspective, and whether decision-making is treated as a binary, staged, or sequential process (Montes De Oca Munguia et al., 2021).

In agricultural contexts, adoption is often viewed as a staged process, where full integration follows a period of learning and experimentation. Factors influencing adoption are typically grouped into individual, technological, social, and economic dimensions (Dissanayake et al., 2022), reflecting paradigms such as innovation-diffusion models (information flow to farmers), adoption-perception models (perceived usefulness and ease of use), and economic constraint models (availability of infrastructure and capital).

Recent scholarship has emphasised the need to integrate both farm-level and system-level perspectives when modelling adoption (Shang et al., 2021). Systemic elements, such as governance structures, stakeholder networks, and market conditions, interact with individual characteristics to shape adoption pathways.

Conceptual frameworks such as the ADOPT model (Kuehne et al., 2017) explicitly account for this interaction, enabling quantitative predictions of adoption rates and timelines. Nonetheless, the statistical significance and effect size of specific factors remain inconsistent across studies, partly due to the underrepresentation of technology-related and systemic variables (Montes De Oca Munguia and Llewellyn, 2020).

Among the less-explored determinants of adoption is farmers' perception of climate change and its impacts. Growing evidence suggests that awareness of climate risks can influence farmers' openness to adopt innovative practices and tools, especially those aimed at improving resilience and sustainability. However, this factor has rarely been integrated into structured behavioural models of technology adoption, leaving a gap in understanding how environmental awareness translates into actual adoption intentions.

Taken together, these insights suggest that no single paradigm is sufficient to capture the full complexity of agricultural technology adoption. Theories and models must be adapted to the objectives and context of each study, selecting factors and interactions that are most relevant to the technology under consideration and the socio-economic environment in which it is introduced.

Against this background, the present study has three main objectives:

1. to analyse the influence of cognitive and dispositional factors on Italian farmers' intention to adopt digital technologies by applying an extended Theory of Planned Behaviour (TPB) framework;
2. to test the influence of two additional constructs: Technical support and Climate change perception, identified in the previous qualitative empirical study as salient drivers of adoption.
3. to examine how adoption intentions translate into actual adoption behaviours, measured both as technology possession and active utilisation.

By integrating attitudinal, systemic, and environmental-awareness factors, the study aims to provide a more comprehensive understanding of the behavioural mechanisms underlying digital technology adoption in the Italian agricultural sector, generating relevant insights for both policy design and targeted stakeholders' engagement strategies.

3.2.2. Theoretical framework and research hypotheses

The Theory of Planned Behaviour (TPB) (Ajzen, 1991) and its decomposed version (Taylor and Todd, 1995b) have been widely applied to explain behavioural intentions in various contexts, including the adoption of agricultural innovations. In its standard formulation, TPB posits that an individual's intention to perform a behaviour is determined by three key constructs: attitude toward the behaviour, subjective norms, and perceived behavioural control.

Attitude reflects the degree to which a person evaluates the behaviour positively or negatively. In agricultural technology adoption, a favourable attitude may arise from perceiving the technology as beneficial for productivity, efficiency, or sustainability. Previous studies have consistently found a positive relationship between attitudes and adoption intentions (Dissanayake et al., 2022; Rezaei et al., 2020).

Subjective norms refer to perceived social pressure from relevant others—such as family members, peers, advisors, or cooperatives—to engage in the behaviour. In agriculture, subjective norms can be shaped by community networks, farmers' associations, or institutional actors (Shang et al., 2021).

Perceived behavioural control captures the extent to which individuals believe they have the resources, knowledge, and ability to perform the behaviour. For farmers, this may include access to financial resources, technical knowledge, and infrastructure (Kuehne et al., 2017).

While the TPB offers a robust framework, several authors have emphasised the importance of extending it with context-specific factors to improve its explanatory power in agricultural settings (Montes de Oca Munguia & Llewellyn, 2020; Osrof et al., 2023).

Evidence from the systematic literature review (Section 2.1) confirmed that the most recurrent and significant determinants of technology adoption in agriculture, can be directly linked to the three core constructs of the Theory of Planned Behavior (TPB): attitudes, subjective norms, and perceived behavioural control. However, it also revealed that TPB-based studies often lack integration of broader systemic variables, resulting in an incomplete representation of the adoption process.

The scoping review on the systemic dimension of adoption (Section 2.2.) further highlighted that systemic factors, such as institutional governance, market conditions, and multi-actor networks, are underrepresented in empirical research, despite being conceptually well-founded and potentially influential (Addorisio et al., 2025b). Among these, technical support and climate change perception emerged as particularly relevant, both theoretically and empirically.

Findings from previous literature and qualitative study (Section 3.1) conducted in Italy reinforced these results. Farmers' intention to adopt digital technologies was found to be shaped not only by their attitudes, perceived norms, and perceived control, but also by the extent to which they can rely on specialized advisory services and by their awareness of climate-related risks (Addorisio et al., 2024; Anastasiou et al., 2023).

Based on this multi-source evidence, the present study adopts an extended TPB framework that incorporates Technical Support and Climate Change Perception as additional exogenous constructs influencing intention.

Technical support, referring to the availability of advisory services, cooperative assistance, and expert consultancy, has emerged as a critical enabler of technology adoption, particularly in contexts where digital tools require specialised skills for effective use. Availability of training, advisory services, and after-sales support can reduce uncertainty, increase perceived ease of use, and ultimately enhance adoption intentions (Gemtou et al., 2024; Kernecker et al., 2020; Pedersen et al., 2024).

Climate change perception reflects farmers' awareness and recognition of climate-related risks and the potential role of technologies in mitigation and adaptation processes. Recent studies suggest that greater awareness of climate change can increase openness to adopting innovative, sustainability-oriented solutions (Niles et al., 2016; Arbuckle et al., 2015), yet its role within structured behavioural models remains underexplored in digital agriculture.

Therefore, the proposed conceptual model (Figure 17) hypothesises that attitudes, subjective norms, perceived behavioural control, technical support, and climate change perception all have direct positive effects on farmers' intention to adopt digital technologies. In turn, behavioural intention is expected to translate into actual adoption, which in this study is operationalised through two complementary dimensions: possession (the acquisition or ownership of digital tools) and utilisation (their effective use in farm operations). This two-step approach acknowledges that owning a technology does not necessarily imply its regular or effective use, and that intention can lead to different adoption outcomes depending on contextual and individual factors.

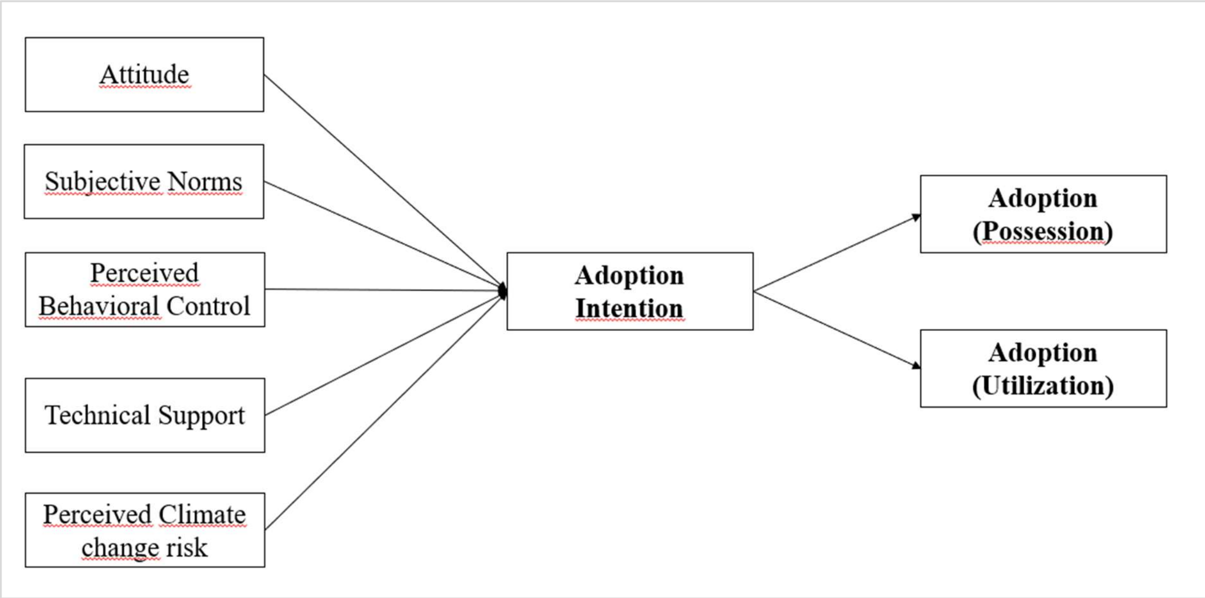


Figure 17 - Conceptual framework

Based on the above reasoning, the following hypotheses are proposed:

- **H1:** Attitude towards digital technologies positively influences farmers' intention to adopt them.
- **H2:** Subjective norms positively influence farmers' intention to adopt digital technologies.
- **H3:** Perceived behavioural control positively influences farmers' intention to adopt digital technologies.
- **H4:** Technical support positively influences farmers' intention to adopt digital technologies.
- **H5:** Climate change perception positively influences farmers' intention to adopt digital technologies.
- **H6:** Farmers' intention to adopt digital technologies positively influences their actual possession of digital technologies (acquisition or ownership)
- **H7:** Farmers' intention to adopt digital technologies positively influences their actual utilization of digital technologies in farm operations

In addition to the main hypotheses, the study also conducted an exploratory analysis of the relationship between farm size and membership in professional organisations. Building on evidence that structural characteristics may condition access to organisational networks (Ramirez, 2013), we examined whether cooperative, producer organisation, and supply chain contract membership were differently associated with farm size.

These extensions allow the model to account for both individual-level determinants and systemic drivers, providing a holistic view of the drivers behind digital technology uptake in agriculture.

3.2.3. Data and Methods

Data collection

Data for this study were collected through an online questionnaire developed on the Qualtrics platform administered among Italian agricultural sector.

The online questionnaire was administered to a sample of Italian farmers and agricultural contractors ("contoterzisti" in italian) to investigate the factors influencing the adoption of digital technologies in agriculture. The survey was distributed online via the most widely used social networking platforms, including WhatsApp, Instagram, and Facebook, in order to maximise reach and engagement. These platforms allowed for efficient data collection across different regions, ensuring broad geographic and demographic coverage.

Data collection took place between September 2024 and March 2025. During this period, respondents could complete the questionnaire at their convenience. A total of 186 valid responses were obtained. Participation was restricted to individuals meeting the inclusion criteria, namely being active farmers or agricultural contractors in Italy.

A convenience sampling approach was adopted to recruit participants, chosen for its practicality in accessing respondents quickly and efficiently. This approach was complemented by the use of social media sharing and network expansion, enabling the survey to reach a larger and more diverse audience within the target population.

The convenience and social-media-based recruitment strategy can increase the likelihood of self-selection into the survey by respondents who are younger, more educated, more digitally exposed, or operating larger farms. As a consequence, respondents may systematically differ from the broader farmer population in terms of farm structure, digital familiarity, and openness towards technology, potentially affecting both descriptive adoption rates and the estimated relationships between behavioural constructs. This potential bias is acknowledged explicitly and is addressed analytically by (i) reporting the socio-demographic profile of respondents, (ii) including key controls (e.g., age and farm size), and (iii) interpreting results as evidence on associations rather than population-wide prevalence estimates.

Following the "tenfold rule" (Hair et al., 2014), the obtained sample size exceeded the minimum threshold required for the complexity of the proposed model.

Measures

The questionnaire was designed based on the extended TPB model presented in the previous section. It aims to measure the determinants of the adoption of digital technologies in Italian agricultural sector and comprised five main sections (Table 16), each dedicated to capture information related to the objective of the study:

Table 16 - Summary of the Questionnaire

SECTIONS	DESCRIPTION
1. Introduction and privacy	General overview of the study Consent and authorization for data processing
2. Control questions	Previous technological knowledge Initial technology endowment and use
3. Data requirements	Data requirements evaluation for individual and aggregate context
4. Structural characteristics	Gender Age Educational level Farm location Farm size Production orientation Membership (cooperatives and/or supply chains)
5. Adoption factors	Attitudinal and systemic factors

Introduction and privacy. The opening part of the questionnaire provided respondents with a general overview of the study and its objectives, along with the necessary information regarding data protection. Informed consent and authorization for data processing were collected in compliance with privacy regulations.

Control and alignment questions. Respondents were first asked to self-assess their level of digital knowledge on a five-point scale (1 = none, 2 = basic, 3 = intermediate, 4 = advanced, 5 = highly specialised). To ensure a shared baseline of understanding, a short description of digital agriculture (Agriculture 4.0) was also provided, highlighting its main components (e.g., sensors, advanced machinery, information systems, artificial intelligence) and its role in supporting farm decision-making. In the empirical model, this variable is treated as an exogenous control to account for heterogeneity in baseline digital familiarity.

Data requirements. A dedicated section investigated respondents' information needs. Farmers were asked to evaluate the usefulness of different types of data for the management of their farm (e.g., crop nutritional status, soil characteristics, input use, environmental resources, meteorological data, labour use, and production data) on a five-point Likert scale (1 = not useful, 5 = indispensable). A complementary block addressed the role of data in supply chain relations, focusing on cultivation practices (e.g., digital farm records), product traceability, environmental performance indicators, and production volumes. These variables are reported descriptively to characterise perceived information needs beyond the farm level.

Structural characteristics. This section gathered information on farmers' age, gender, education level, and structural and organisational aspects of the farm, including farm size, type of farming system, geographic location and participation in professional associations or cooperatives.

Technology possession and use. Respondents were asked to indicate whether they owned or used a set of digital technologies commonly applied in agriculture, such as GPS-guided machinery, remote sensing, farm management information systems, variable rate technologies, drones, and IoT-based monitoring systems. Possession and usage were recorded separately to distinguish between availability and current adoption.

TPB constructs and extended factors. The core of the questionnaire was dedicated to measuring constructs from the Theory of Planned Behaviour. Specifically:

1. Attitude (ATT) – measured with three items (ATT1, ATT 2, ATT 3) capturing farmers' overall evaluation of digital technologies in terms of usefulness, efficiency, and expected benefits.
2. Subjective Norms (SN) – measured with three items (SN1, SN 2, SN 3) assessing perceived social pressure and expectations from peers, family, advisors, and cooperatives.

3. Perceived Behavioral Control (PBC) – measured with four items (PBC1, PBC2, PBC3, PBC4) referring to farmers' perceived ease or difficulty in adopting digital technologies, considering skills, resources, and compatibility with existing systems.
4. Intention to Adopt (INT) – measured with three items (INT1, INT2, INT3) capturing the strength of farmers' intention to adopt digital technologies in the near future.

In addition, two constructs identified as relevant in previous phases of the research were included:

1. Technical Support (availability and quality of advisory and maintenance services) (SUPP) – measured with three items (SUPP1, SUPP2, SUPP3) reflecting the availability and quality of specialized advisory services, technical assistance, and training opportunities.
2. Climate Change Perception (perceived relevance of climate risks and their impact on farming decisions) Climate Change Perception (CCP) – measured with five items (CCP1 to CCP5) assessing farmers' awareness of climate risks and belief in the role of digital technologies for mitigation and adaptation.

Finally, to examine how adoption intentions translate into actual adoption behaviours, two additional measures were included:

3. Actual Adoption (ADOPT) – measured as a binary variable, separately for technology ownership and use, based on self-reported possession and operational implementation of selected digital tools in farm activities.

Combining the two answers yields four mutually exclusive adoption states: BEST (owned and used), WORST (owned but not used), External use (used but not owned, e.g., via contractors/service providers), and Nothing (neither owned nor used). To summarise adoption intensity across technologies, two composite indices were constructed: Adoption Own, computed as the proportion of technologies owned out of the total set considered, and Adoption Use, computed as the proportion of technologies actively used.

All constructs were operationalized using multi-item measures adapted from previous studies on agricultural technology adoption and TPB applications. Respondents expressed their agreement with each statement on a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree") (Table 17).

Table 17 - Model constructs (originally administrated in Italian)

Constructs	Items	Reference
Intention (INT)	I plan to use digital technologies this year	(Kakkavou et al., 2024)
	I intend to use digital technologies for the next 5 years.	
	I will use digital technologies regularly in the future.	
Attitude (ATT)	I think that the use of digital technologies in crop production can increase profitability of my farm.	(Feisthauer et al., 2024)
	I think that the use of digital technologies in crop production can be advantageous for my farm.	
	I think that the use of digital technologies in crop production may prove to be useful for my farm.	
	I think that the use of digital technologies in crop production would not be worth it for my farm.	
Subjective norms (SN)	People who are important to me regarding my business decisions on farm think that I should use digital technologies.	(Venkatesh et al., 2012)
	People who influence my business decisions on farm think that I should use digital technologies.	
	People whose opinion regarding my farming business decisions I value think that I should use digital technologies.	
Perceived behavioral control (PBC)	It is easy for me to find the information I need for the use of digital technologies in my cultivation.	(Kakkavou et al., 2024)
	I have the technical skills to implement digital technologies in my cultivation.	
	I can afford the financial expenses for the implementation of digital technologies in my cultivation.	
	I have the time to dedicate to the use of digital technologies for my cultivation.	
Perceived climate	I believe that climate change is real	
	The main causes of climate change are human activities	

change risk (CCP)	Climate change will lead to serious negative consequences	(van Valkengoed et al., 2021)
	The area where I live will be affected by climate change	
	It will take a long time before the consequences of climate change become apparent	
Technical Support (SUPP)	I think I would need greater technical support to use digital technologies in my farm	
	I think greater technical support would improve my ability to use digital technologies in my farm	
	I think greater technical support would allow me to keep up with technological advancements	

To capture actual adoption in greater detail, the questionnaire distinguished between possession and use of digital technologies. In the first question, respondents were asked to indicate whether they currently possessed specific digital tools within their farming activities (e.g., unmanned vehicles such as robots or drones, farm management information systems, decision support systems, cloud-based data storage, smart tractors with guidance and ISOBUS/CANBUS, proximal sensors, satellite imagery, and mobile digital devices). In the second question, they were asked whether they actively used each of the technologies listed. Both possession and use were measured through binary items (Yes/No), allowing for the identification of potential gaps between ownership and effective utilisation of digital technologies in agricultural practice. Subsequently, two composite indices were constructed: "Adoption Own", calculated as the proportion of technologies possessed over the total number of technologies considered, and "Adoption Use", calculated as the proportion of technologies actually used.

Let K denote the total number of digital technologies considered in the questionnaire. The two composite indicators were computed as:

$$Adoption\ Own_i = \frac{\sum_{k=1}^{K} Own_{ik}}{K}, \qquad Adoption\ Use_i = \frac{\sum_{k=1}^{K} Use_{ik}}{K},$$

where $Own_{ik} = 1$ if farmer i owns technology k (0 otherwise), and $Use_{ik} = 1$ if farmer i actively uses technology k (0 otherwise). Each technology was assigned the same weight, consistently with the technology-neutral approach adopted in this research, which aims to capture overall adoption intensity without referring to specific tools.

These indices, ranging from 0 to 1, provide a continuous measure of the degree of digital technology adoption, distinguishing between availability and operational implementation.

Data analysis

The dataset was then prepared for statistical analysis, including screening for missing values, coding of categorical variables, and assessment of assumptions, before proceeding to the measurement and structural model evaluation.

The hypothesized relationships were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the cSEM package in R Software. This method was chosen for its suitability in exploratory research with complex models and its ability to handle both reflective and formative constructs without requiring multivariate normality (Russo and Stol, 2021).

The analysis followed a two-step approach: (1) Measurement model evaluation, to assess indicator reliability (outer loadings), internal consistency (Cronbach's alpha, composite reliability), convergent validity (Average Variance Extracted, AVE), discriminant validity (Fornell–Larcker criterion and HTMT ratio) and multicollinearity (Variance Inflation Factor (VIF); (2) Structural model evaluation, estimating path coefficients and their significance via bootstrapping with 5,000 resamples, and assessing explanatory power (R^2), predictive relevance (Q^2), and effect sizes (f^2).

Items that did not meet reliability or validity thresholds were removed from the analysis, in order to improve the robustness of the measurement model while preserving theoretical consistency. Specifically, within the Attitude construct, item Attitude_2 was removed due to collinearity issues, which inflated its variance inflation factor (VIF) above recommended thresholds. Consistent with PLS-SEM guidelines (Hair et al., 2014), its exclusion improved reliability and discriminant validity, while the remaining indicators continued to capture the intended construct domain.

Within the Climate Change Perception construct, item Climate_5 exhibited a near-zero loading (-0.01), indicating no contribution to the latent variable and substantially reducing its convergent validity (AVE = 0.478). In line with established recommendations (Hair et al., 2014), Climate_5 was removed, resulting in a construct with acceptable reliability (Cronbach's $\alpha = 0.708$; $\rho C = 0.778$) and preserved conceptual coherence, as the remaining four indicators continued to reflect farmers' awareness of climate risks and their implications for technology adoption.

Finally, in order to test indirect effects (mediation analysis), we complemented the PLS-SEM results with causal mediation models estimated through the mediation package in R (Imai et al., 2010). The analysis focused on the role of Subjective Norms and Perceived Behavioural Control as mediators of the relationship between membership in professional organisations and farmers' Intention to adopt digital technologies. For each mediation path, the Average Causal Mediation Effect (ACME), the Average Direct Effect (ADE), and the Total Effect were estimated.

In addition to the previous analyses, a complementary set of logistic regression models was estimated to examine the relationship between farm size and membership in professional organisations (W. Hosmer, 2013). Membership (binary) was used as the dependent variable, with farm size as the independent variable. Competing model specifications (Greene, 2020) were tested: (i) continuous farm size, (ii) categorical classes (<20 ha, 20–49 ha, 50–99 ha, ≥100 ha), and (iii) non-linear spline transformations. Model performance was compared using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Burnham and Anderson, 2004), allowing the identification of the most appropriate functional form for each membership type. This additional step enabled the analysis to assess whether organisational participation is uniformly distributed across farm sizes or whether structural thresholds and discontinuities exist.

Statistical inference was based on non-parametric bootstrapping with 5,000 resamples, and significance was assessed by verifying whether the 95% confidence intervals excluded zero. This procedure allowed to disentangle direct and indirect effects and to quantify the proportion of the total effect explained by the mediators.

The model was estimated in two stages: first, with Intention as the dependent variable, and subsequently by including the Adoption construct to assess the relationship between Intention and Adoption.

3.2.4. Results

The final sample consisted of 186 Italian farmers, covering all major production systems, including arable crops, livestock, and mixed farming. The respondents were geographically distributed across the main agricultural regions of Italy, ensuring coverage of both northern and southern areas. Table 18 shows the descriptive statistics of the socio-demographic variables.

The average age was 45,6 years (SD = 13.8), with 78.9% of respondents under 45 years old. Males represented 79% of the sample, and 89.8% of farmers held at least a secondary education degree. Farm size was highly heterogeneous, with a median of 30 hectares (IQR = 67.5). About 88% of respondents managed farms larger than 50 hectares, while the remainder were distributed across smaller size classes. In terms of location, farms were mainly situated in plain areas (46.2%), followed by hills (35.5%), mixed areas (9.7%), and mountains (8.6%). Geographically, 38.2% of the sample was located in Northern Italy, 25.3% in Central Italy, and 36.6% in Southern Italy.

With regard to production orientation, crop farming predominated (82.3%), while 13.4% of respondents operated mixed farms and only 4.3% specialized in livestock. Participation in collective organizations was limited: 40.9% reported no membership, while 28% held one membership, 22% two, and only 9.1% three memberships. The use of farm contracting (contoterzismo) was mostly absent (76.3%), though 18.8% practiced it occasionally, and only a small minority reported frequent (3.2%) or exclusive (1.6%) reliance on external service providers.

Technological knowledge was generally modest: 24.7% declared only basic competences, 44.1% intermediate, and 21.5% advanced, while a small group reported highly specialized skills (2.7%). Only 7% declared having no knowledge at all.

The achieved sample is skewed towards younger respondents and larger farms, suggesting that small and older farms may be underrepresented. Therefore, prevalence estimates and average levels of intention should be interpreted as referring to this sample rather than to the entire farmer population. The overrepresentation of large farms may also attenuate the visibility of constraints that are more salient in smaller holdings, such as limited capital, time, and access to skills.

Table 18 - Sample characteristics and technology adoption (N = 186)

Variables		Sample (N)	%
Age of respondent			
	Mean (SD)	45.6 (13.8)	
	< 45 years	147	79
Gender			

Male	147	79
Female	35	18.8
Others	4	2.2
Educational level		
Secondary or higher	167	89.8
Less than secondary	19	10.2
Farm size		
(median and IQR)	30 (67.5)	
Farm size by classes		
< 9.99		1.1
10–19.99		2.5
20–29.99		2.0
30– 49.99		6.3
50–99.99		11.0
>100		77.1
Farm location		
Plane	86	46.2
Hill	66	35.5
Mountain	16	8.6
Mixed	18	9.7
Geographical area		
Northern Italy	71	38.2
Central Italy	47	25.3
Southern Italy	68	36.6
Production orientation		
Crop farming	153	82.3
Livestock	8	4.3
Mixed farming	25	13.4
Membership		
None	76	40.9
One	52	28

Two	41	22
Three	17	9.1
Farm contracting		
Not practiced	142	76.3
Occasionally practiced	35	18.8
Frequently practiced	6	3.2
Prioritized/Exclusively practiced	3	1.6
Technological knowledge		
None	13	7
Basic	46	24.7
Intermediate	82	44.1
Advanced	40	21.5
Highly specialized	5	2.7

With respect of technology adoption, measured as initial technology endowment and use, the joint analysis of ownership and use of digital technologies reveals marked heterogeneity across solutions (Figure 18).

In particular, 84% of farmers reported owning at least one digital technology, while 72% declared actual use. The most owned tools were GPS-guided machinery (65%), remote sensing (54%), and farm management information systems (48%). The gap between ownership and actual use was particularly evident for advanced tools such as drones (30% ownership vs. 12% use) and IoT-based monitoring systems (28% vs. 10%)The most frequent category is “Nothing” (neither ownership nor use), which is predominant for robots/drones (90%), decision support systems – DSS (65%), smart tractors (70%), and satellite imagery (70%).

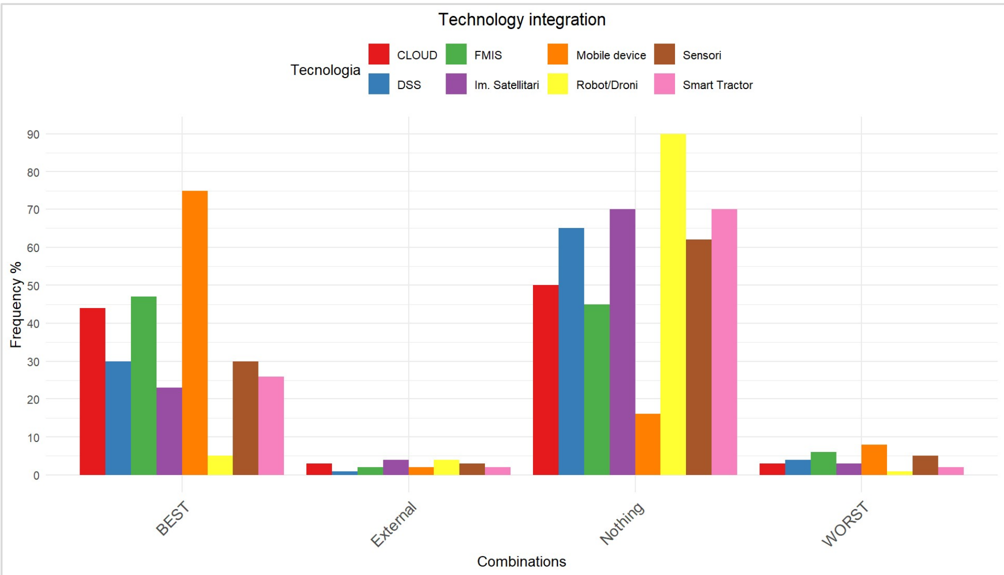
Instances of full adoption (“BEST”: ownership and use) emerge more clearly for mobile devices (75%), followed by FMIS (47%), cloud computing (44%), sensors (30%), and DSS (30%). Conversely, more advanced and specialized technologies such as robots/drones and smart tractors display limited levels of combined ownership and use (5% and 26%, respectively).

The “WORST” condition (ownership without use) is not negligible for some technologies, such as mobile devices (8%) and FMIS (6%), suggesting the presence of barriers to the effective exploitation of tools already available on farms.

To a lesser extent, cases of “External use” (use without ownership) are observed, particularly for robots/drones (4%) and satellite imagery (4%), where access to services is likely mediated by external providers or shared platforms.

Overall, the results highlight a clear distinction between technologies that are already consolidated in practice (notably mobile devices, but also FMIS and cloud solutions) and those still perceived as frontier innovations (robots/drones, smart tractors, satellite imagery), for which non-adoption or partial adoption remain the dominant patterns.

Figure 18 - Technology Adoption



In terms of data requirements, farmers were asked to evaluate their needs both at farm and supply chain level.

At the farm level (Table 19), the most critical needs are related to Weather Data (M=4.13; SD=0.80) and Productivity (M=4.06; SD=0.81), with more than 80% of farmers rating them as very useful or indispensable. These are followed by Soil Characteristics (M=3.82; SD=0.80) and Nutritional Status (M=3.77; SD=0.85), both considered highly relevant for monitoring and improving farm performance.

Intermediate values are observed for Labor Use (M=3.56; SD=1.04) and Inputs (M=3.66; SD=0.92), while Environmental Resources (M=3.35; SD=0.98) ranks lowest, though still above the neutral midpoint of the scale.

Table 19 - Farm-level data requirements (Farmers' perceived data needs for farm management)

DATA	Mean	SD
Weather	4.13	0.80
Productivity	4.06	0.81
Soil Characteristics	3.82	0.80
Nutritional Status	3.77	0.85
Inputs	3.66	0.92
Labor Use	3.56	1.04
Environmental Resources	3.35	0.98

For supply chain relations (Table 20), the highest scores are reported for Productivity (M=3.79; SD=0.97) and Traceability (M=3.69; SD=1.04), with about two-thirds of farmers ranking them as very useful or indispensable. Agricultural Practices (M=3.56; SD=0.95) holds an intermediate position, while Inputs (M=3.37; SD=1.03) and Environmental Performance (M=3.32; SD=1.02) appear less salient, though still above the neutral midpoint.

Table 20 - Supply chain-level data requirements (Farmers' perceived data needs for supply chain relations)

Data	Mean	SD
Productivity	3.79	0.97
Traceability	3.69	1.04
Agricultural Practices	3.56	0.95
Inputs	3.37	1.03
Environmental Performance	3.32	1.02

The measurement model was assessed on the basis of convergent and discriminant validity (Table 21). The reliability and validity of the constructs were first assessed through the evaluation of indicator loadings, internal consistency reliability, convergent validity, and discriminant validity.

During the assessment of the measurement model, two items were removed because they did not meet the reliability and validity thresholds. Within the Attitude construct, item Attitude_2 showed collinearity issues, inflating its variance inflation factor (VIF) and weakening discriminant validity. Its exclusion improved the psychometric properties of the construct, while the remaining items continued to capture farmers’ evaluative orientation toward digital technologies. Within the Climate Change Perception construct, item Climate_5 exhibited a near-zero loading (-0.01), providing no contribution to the latent factor and lowering the Average Variance Extracted (AVE). Following established SEM guidelines, Climate_5 was removed, which led to satisfactory reliability and convergence for the construct, while preserving its conceptual coherence through the remaining four indicators.

A part of CCP2 (0.569), all item loadings exceeded the recommended threshold of 0.70, confirming that they adequately represent its associated latent construct. Although the climate perception construct contains an item with a loading below the threshold, it demonstrated excellent reliability and convergence values. Therefore, it was deemed appropriate to retain it in the model.

Internal consistency reliability, assessed using Cronbach’s alpha and Composite Reliability (CR), yielded values above 0.70 for all constructs, indicating satisfactory reliability. Convergent validity was confirmed as the Average Variance Extracted (AVE) values were all above 0.50, suggesting that each construct explains more than half of the variance of its indicators.

Discriminant validity was evaluated using the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio of correlations (HTMT). The Fornell–Larcker criterion showed that the square root of the AVE for each construct was greater than the correlations with other constructs, confirming discriminant validity. HTMT values were all below the conservative threshold of 0.85, further supporting the distinctiveness of the constructs.

Finally, collinearity diagnostics assessed through Variance Inflation Factor (VIF) indicated no critical multicollinearity issues, as all VIF values were below the recommended threshold of 5. Therefore, it can be concluded that the measurement model employed in this study fully meets the required criteria for internal consistency reliability, convergent validity, and discriminant validity, thus providing a robust and reliable foundation for the subsequent structural model analysis.

Table 21 - Reliability and validity tests

Latent Construct	**Items**	**Outer loadings**	**Cronbach's alpha**	**Composite Reliability (CR)**	**AVE**
Intention (INT)	INT1	0.815	0.875	0.923	0.800

	INT2	0.953			
	INT3	0.911			
Attitude (ATT)	ATT1	0.870	0.777	0.898	0.814
	ATT3	0.933			
Subjective norms (SN)	SN1	0.884	0.870	0.921	0.795
	SN2	0.926			
	SN3	0.863			
Perceived behavioural control (PBC)	PBC1	0.819	0.785	0.861	0.607
	PBC2	0.763			
	PBC3	0.737			
	PBC4	0.795			
Technical support (SUPP)	SUPP1	0.865	0.886	0.929	0.813
	SUPP2	0.923			
	SUPP3	0.916			
Climate change perception (CCP)	CCP1	0.774	0.871	0.858	0.611
	CCP2	0.569			
	CCP3	0.745			
	CCP4	0.983			

On this basis, the analysis proceeds to the assessment of the structural model that aims to test the hypothesised relationships between latent constructs and to determine the model's explanatory and predictive power.

In this study, the assessment was conducted analysing the variance explained (R^2), the model's predictive relevance (Q^2), the statistical significance of path coefficients, and finally the effect sizes (f^2) of each predictor.

As shown in Table 22 the model explained a substantial proportion of the variance in the main dependent variables, with R^2 values of 0.597 for Intention to Adopt, 0.237 Adoption by possession, and 0.229 for Adoption by utilization of digital technologies.

The Stone–Geisser Q^2 assesses the model's predictive accuracy using blindfolding procedures. Positive Q^2 values indicate that the model has predictive capability beyond mere data fitting. All endogenous constructs reported positive Q^2 values (Intention_1 = 0.243; Intention_2 = 0.501; Intention_3 = 0.501), confirming satisfactory predictive relevance.

Moreover, the global Goodness-of-fit (GoF) index that summarises the overall fit of the model, combining measurement and structural model quality, was 0.725, indicating a large overall fit and strong model adequacy.

The f^2 statistic measures the relative contribution of each predictor to the R^2 of the corrsponding endogenous construct. The analysis revealed that Attitude ($f^2 = 0.311$) had a moderate-to-large effect and Perceived Behavioural Control ($f^2 = 0.063$) a small-to-moderate effect on Intention, whereas Subjective Norms ($f^2 = 0.008$), Climate Change Perception ($f^2 = 0.000$), and Technical Support ($f^2 = 0.040$) exerted small yet non-negligible effects.

Table 22 - Summary of the structural model

Hypothesis	Path	β	p-value	f^2	Q^2	Supported
H1	Attitude → Intention	0.463	< 0.001	0.311	0.320	Yes
H2	Subjective Norms → Intention	0.069	0.301	0.006	0.320	No
H3	Perceived Behavioural Control → Intention	0.219	0.001	0.063	0.320	Yes
H4	Technical Support → Intention	0.144	0.018	0.040	0.320	Yes
H5	Climate Change Perception → Intention	0.001	0.989	0.000	0.320	No
H6	Intention → Possession	0.125	< 0.001	0.237	0.340	Yes
H7	Intention → Use	0.124	< 0.001	0.230	0.325	Yes

Bootstrapping with 5.000 resamples was employed to assess the significance of path coefficients and to test the proposed hypotheses, Results indicated that two of the three core Theory of Planned Behaviour (TPB) constructs had significant and positive effects on farmers' Intention to adopt digital technologies. Specifically, Attitude (H1) showed the strongest effect ($\beta = 0.463$, $p < 0.001$), followed by Perceived Behavioural Control (H3) ($\beta = 0.219$, $p = 0.001$), both supporting the corresponding hypotheses.

Conversely, Subjective Norms (H2) did not exert a statistically significant effect on Intention ($\beta = 0.069$, $p > 0.05$), thus not supporting H2.

Among the extended constructs, Technical Support (H4) had a positive and significant direct effect on Intention ($\beta = 0.144$, $p < 0.005$), confirming that advisory services, training, and after-sales assistance directly foster adoption readiness, Conversely, Climate Change Perception (H5) did not show a statistically significant direct effect on Intention ($\beta = 0.001$, $p > 0.05$).

The final step assessed the relationship between farmers' Intention and their actual adoption behaviour, measured as both Possession and Use of digital technologies. The two additional regression analysis revealed that Intention significantly influenced both Possession (H6) ($\beta = 0.125$, $p < 0.001$) and Use (H7) ($\beta = 0.124$, $p < 0.001$) of digital technologies, confirming that stronger behavioural intentions translate into both acquiring and actively using such tools. The explained variance (R^2) was 0.237 for Possession and 0.230 for Use, with effect size (f^2) values indicating large effects for Intention on both outcomes.

Mediation analysis further clarified the role of indirect effects. Membership in organisations exerted significant indirect effects on farmers' Intention through both Subjective Norms and Perceived Behavioural Control. In particular, membership in producer organisations showed a significant mediation through Norms (ACME = 0.139, $p < 0.05$) and a positive total effect ($p < 0.001$), while membership in professional associations revealed significant mediation through Norms (ACME = 0.160, $p < 0.05$) despite a non-significant direct effect. By contrast, mediation through Perceived Behavioural Control was weaker and generally non-significant, except for a marginal effect of professional association membership ($p \approx 0.05$).

Overall, these results indicate that organisational membership primarily operates by reinforcing normative pressures, rather than enhancing perceived behavioural control.

The analysis also examined the effects of socio-demographic characteristics on farmers' intention to adopt digital technologies. Among the variables considered: gender, age, education level, geographical location, farm size, and farming system, only farm size showed a statistically significant effect.

Specifically, larger farms were associated with higher adoption intentions ($\beta = 0.086$, $p < 0.05$), with an effect size (f^2) below 0.02, indicating a small but statistically significant contribution. All other socio-demographic variables had small and statistically non-significant effects: technological knowledge (Know) ($\beta = 0.058$, $p > 0.05$), gender ($\beta = -0.016$, $p > 0.05$), age ($\beta = -0.079$, $p > 0.05$), education level ($\beta = 0.080$, $p > 0.05$), geographical location ($\beta = -0.046$, $p > 0.05$), and production orientation ($\beta = -0.045$, $p > 0.05$). Corresponding effect size (f^2) values for these variables were all below 0.02, indicating negligible contributions to the explained variance in intention.

Complementary logit analyses further clarified the role of farm size in conditioning organisational participation (Table 23). For cooperative and producer organisation membership, the effect of size was weak and best captured by non-linear spline models, suggesting that participation is relatively accessible across farm scales without clear thresholds. By contrast, contract farming schemes were best explained by a categorical specification, indicating the existence of structural thresholds: medium and large farms displayed significantly higher probabilities of participation compared to small farms. These findings indicates that in this sample while cooperative and producer organisation membership operates independently of farm scale, access to supply chain contracts is conditioned by structural capacity.

Table 23- Model fit comparison for logistic regressions of farm size on organisational membership

Membership type	Model specification	AIC	BIC
Cooperatives	Continuous (logit)	248.37	254.82
	Classes	251.83	261.51
	Spline (df=3)	247.91	260.81
Producer Organisations	Continuous (logit)	240.72	247.17
	Classes	241.72	251.39
	Spline (df=3)	239.38	252.28
Contract farming schemes	Continuous (logit)	217.79	224.24
	Classes	196.73	206.40
	Spline (df=3)	201.03	213.94

Overall, the results indicate that farmers' behavioural intention is shaped mainly by attitudinal and social factors, with farm size being the only socio-demographic attribute of note, Systemic factors, such as Technical Support, also contribute meaningfully. The strong link between intention to adopt and both possession and use of digital technologies confirms its key role as a direct driver of actual adoption.

4. Discussion

This research aimed to investigate the determinants of farmers' adoption of digital technologies by integrating individual, technological, and systemic dimensions, addressing the knowledge gaps identified in the literature. In particular, the study sought to (i) map factors and theoretical frameworks in technology adoption process, (ii) explore the systemic domain of technology adoption and its operationalisation, (iii) elicit stakeholders' perceptions of barriers and drivers, and (iv) empirically test an extended behavioural model that incorporates systemic constructs.

The thesis integrates evidence across three empirical phases to progress from identifying which determinants are associated with adoption intentions to explaining how and why these determinants operate within a specific socio-technical system. The systematic review synthesises the dominant behavioural drivers reported in the literature and highlights the limited use of explicit theoretical frameworks; the scoping review documents the comparatively infrequent operationalisation of systemic determinants; stakeholder interviews elucidate how systemic constraints are experienced, interpreted, and negotiated by actors across the agri-food value chain; and the survey quantifies the relative contribution of individual-level determinants and enabling conditions to farmers' adoption intention.This chapter provides an integrated discussion of the results emerging from the different components of the research: the two literature reviews, the explorative study with Italian stakeholders, and the quantitative analysis based on the Theory of Planned Behavior (TPB) extended with systemic constructs.

The general literature review (Chapter 2.1) mapped the determinants of agricultural technology adoption and the theoretical frameworks most used to explain diffusion processes, identifying a large and growing body of literature on the topic. It revealed that most studies are concentrated on individual-level factors (Hüttel et al., 2022; Li et al., 2023; Michels et al., 2020; Monteleone et al., 2020) such as attitudes, perceptions, skills, and human capital, which together accounted for nearly half of all distinct factors and article mentions. By contrast, organisational (Michels et al., 2020; Song et al., 2022), technological (Berthold et al., 2021; Tran et al., 2023; Vecchio et al., 2020), and institutional (Agnusdei et al., 2023; Li et al., 2023; Troiano et al., 2023) determinants received more limited attention, often framed in relation to specific constraints such as investment costs, compatibility issues, or policy support. Systemic drivers (Agnusdei et al., 2023; Blasch et al., 2021; Giua et al., 2022; Kenny and Regan, 2021), including governance, actor networks, and data-sharing infrastructures, were comparatively underrepresented, representing only about one quarter of the factors identified.

Moreover, the review showed that fewer than one-third of the studies (Caffaro et al., 2020; Hüttel et al., 2022; Vecchio et al., 2020) explicitly used a theoretical framework, with the TPB being the most common but seldom extended to include meso- or macro-level variables. This finding reinforces the knowledge gap identified in the background of the thesis, underscoring the need to explicitly incorporate systemic elements into behavioural models to more accurately capture the complexity of technology adoption processes (Eastwood and Rue, 2017; Shang et al., 2021).

The scoping review (Chapter 2.2) focused on the systemic dimension of adoption, mapping 52 unique factors and showing that while publications addressing system-level issues have grown rapidly since 2019, they remain fragmented and conceptually inconsistent. Only about 20% of studies (Giagnocavo et al., 2025; Parra-López et al., 2024; Yeo and Keske, 2024) adopted an explicit theoretical lens, and fewer still provided operational definitions of system-related constructs such as governance, cooperation, or enabling infrastructures. Key factors emerging from the review included actor interactions, data interoperability, access to financial support, and technical assistance, elements that were repeatedly cited in the Background as underexplored drivers of digitalisation (McGrath et al., 2023; Shang et al., 2021). The review therefore substantiated the need to empirically examine how these systemic factors influence farmers' behaviour.

The qualitative study (Chapter 3.1) confirmed the relevance of these factors, providing granular insights into their Italian context manifestation. Italian stakeholders identified several barriers (Addorisio et al., 2025a) that align with those mapped in the reviews, including high investment costs, lack of awareness of technology benefits, cultural resistance, insufficient technical support and structural constraints such as farm size, specialisation, and biophysical conditions. Among the drivers, participants highlighted the potential to improve farm profitability, respond to regulatory and market demands, enhance environmental performance and leverage cooperation within the supply chain. Nevertheless, they consistently called for Decision Support Systems (DSS) to manage data integration and for training and advisory services to reduce complexity, aligning with major evidence from the previous literature (Gemtou et al., 2024; Monteiro Moretti et al., 2023).

The quantitative analysis (Chapter 3.2) empirically validated several of the hypothesised relationships derived from the reviews and the qualitative phase. Attitude and perceived behavioural control were the strongest predictors of intention, confirming the central role of these constructs in the TPB. Subjective norms did not exert a statistically significant effect, suggesting that peer influence plays a limited role in this context. Among the systemic constructs, technical support was found to have a direct positive effect on intention, reinforcing the evidence from stakeholders and literature that advisory services are crucial enablers of digitalisation (Gemtou et al., 2024). Membership influenced intention indirectly through norms, with only marginal mediation via control, indicating that organisational affiliation shapes both perceived expectations and farmers' sense of capacity. Complementary logit–probit analyses further revealed that cooperative and producer organisation membership was only weakly associated with farm size and followed a non-linear pattern without sharp thresholds, while contract farming schemes displayed a strong size-related effect, with medium and large farms significantly more likely to participate. This points to a two-level mechanism: participation in contracts is structurally conditioned by farm size, and once membership is established, it reinforces the normative and control pathways that feed into adoption intention.

By contrast, climate change perception did not show any significant direct effect, suggesting that, in this sample, environmental awareness alone was not sufficient to increase adoption intention.

Among socio-demographic variables, only farm size showed a significant effect, with larger farms being more likely to intend adoption, albeit with a small effect size.

Finally, the regression of intention on adoption confirmed that intention is a significant predictor for both technology ownership and usage, supporting the assumption that behavioural intention is a proximal determinant of actual behaviour (Ajzen, 1991). This finding directly addresses one of the primary endpoints specified in the Methods section and validates the use of TPB as a predictive framework.

Taken together, these findings reinforce the idea that digital technology adoption is best understood as a socio-technical process. Attitude was found to be the strongest predictor of intention, confirming the central role of this construct in shaping behavioural outcomes. This result aligns with Ajzen's (1991) Theory of Planned Behavior and with previous research highlighting perceived usefulness and expected performance improvements as key drivers of adoption (Fragomeli et al., 2024; Osrof et al., 2023).

From a practical perspective, this suggests that strategies to foster adoption should prioritise demonstrating tangible benefits of digitalisation, for instance through field trials, farm demonstration networks, and peer-to-peer learning. Stakeholders in the qualitative phase emphasised that many farmers remain unconvinced of the economic advantage of digital tools. Addressing this perception gap may therefore significantly increase adoption intention.

Perceived behavioural control also showed a strong positive effect on intention, underlining that adoption depends on farmers' confidence in their ability to integrate technologies into their work systems. This confirms the findings of the scoping review that capability factors, such as digital literacy, access to skilled labour, and interoperability, are decisive enablers (Shang et al., 2021).

The qualitative study revealed that lack of training and advisory support is a major barrier, which explains why control perceptions are decisive in predicting intention. This finding calls for investment in training, simplified user interfaces, and stronger integration of digital tools into existing workflows to reduce complexity and build confidence.

Subjective norms did not exert a significant influence, indicating that social pressure from peers, advisors, or supply chain actors was weaker than expected. While norms are often considered a strong determinant of behaviour in collective settings (Song et al., 2022; Sun et al., 2022), their limited effect in this study may be attributed to the structural characteristics of Italian agriculture, where high farm fragmentation and relatively low density of formal innovation networks in the Italian agricultural sector, weaken the influence of peer effects and limits the visibility of early adopters. Stakeholders also pointed out that cooperation remains underdeveloped and that farmers often rely on individual decision-making. Therefore, strengthening innovation networks and cooperative structures could amplify the role of social norms in accelerating technology diffusion (Monteiro Moretti et al., 2023; Pedersen et al., 2024).

The most novel contribution of this research lies in the inclusion of systemic factors in the model. The significance of technical support in shaping farmers' adoption intention underscores its enabling role in reducing complexity and building farmers' confidence. This result confirms stakeholder statements that advisory services and technical assistance are critical for overcoming complexity and increasing technology uptake, also aligning with literature calling for greater investment in extension services (Gemtou et al., 2024; Kernecker et al., 2020). The implication is that strengthening public and private extension systems could be a highly effective policy lever. This includes not only classical training but also continuous support mechanisms, hotlines, and on-farm demonstrations, which were repeatedly mentioned by stakeholders as decisive.

Another noteworthy finding is the lack of a significant association between climate change perception and intention, indicating that awareness of climate risks did not directly motivate farmers in this sample to adopt digital technologies. This contrasts with recent reviews of climate-smart agriculture adoption, which point to risk perception as a key motivator for behavioural change (Gemtou et al., 2024). However, it is consistent with the qualitative study, where climate change was not identified as a primary driver of adoption. Italian stakeholders referred to it mainly as a secondary environmental benefit, often linked to economic efficiency (e.g., soil fertility, input optimisation), rather than as a direct motivator. This discrepancy highlights the importance of contextual factors and suggests that, in the Italian context, profitability and technical support play a more decisive role in shaping adoption intentions.

Membership in cooperatives, associations, or other collective organisations did not directly predict intention but had an indirect effect through norms, with control playing only a marginal role.

This finding highlights the dual role of membership: (i) it increases exposure to information and peer expectations (raising subjective norms), and (ii) it provides access to shared services, training, and cost-sharing schemes (enhancing control).

The complementary logit analysis further explored the relationship between farm size and organisational affiliation. Results indicated that for cooperatives and producer organisations, the effect of farm size was weak and best captured by non-linear (spline) models, suggesting that membership is relatively accessible across different scales, without clear thresholds. By contrast, contract farming schemes were best explained by a categorical specification, pointing to the existence of size thresholds: medium and large farms showed significantly higher probabilities of membership compared to small farms.

This finding integrates with the TPB results, where contract membership indirectly influenced intention through subjective norms and, marginally, control. Taken together, the analyses suggest that while cooperative and producer organisation membership exerts an influence independent of scale, access to contract farming is structurally conditioned by farm size.

These results resonate with network-based studies (Ramirez, 2013), which highlighted that organisational participation is a key driver of technology adoption, but that participation itself is mediated by structural factors such as ownership or resource endowment. In the Italian case, contracts of filiera appear to represent such selective networks, where only farmers with sufficient scale are able to join, and where network effects then reinforce normative and capability-related drivers of adoption.

This result validates the systemic perspective of the scoping review, which called for greater attention to meso-level actors as mediators of technology uptake (McGrath et al., 2023). Encouraging farmers to participate in formal networks may therefore be a lever to amplify both social and capability drivers.

These findings also resonate with the broader literature on social capital as a lever for innovation diffusion. As highlighted by Barbuto et al, (2019), organisational structures such as cooperatives, producer organisations, and contract schemes can function as vehicles for social learning, reducing policy costs and increasing the impact of rural development measures. In this perspective, contract farming networks, while selective, may act as powerful multipliers once thresholds of participation are reached, whereas cooperatives and producer organisations provide more inclusive platforms for peer-to-peer diffusion. This interpretation is consistent with recent evidence from Operational Groups in Italy (Mazzulla and Raggi, 2025), which demonstrated that structured multi-actor collaborations can directly improve farm economic performance. Such findings confirm that beyond their indirect role in shaping norms and control, collective organisations can also function as systemic enablers that generate tangible benefits for participating farms.

The analysis also highlighted that larger farms were more inclined to adopt digital technologies, confirming the role of structural capacity as an enabling condition, although the effect was small.

Finally, the significant regression of intention on adoption (both for technology ownership and use) confirms that intention is a proximal determinant of behaviour, as postulated by TPB theory (Ajzen, 1991). Importantly, this finding shows that a well-specified behavioural model can effectively predict not only intention but also actual adoption behaviour in the field.

However, the observed discrepancy between ownership and actual use of technologies (Figure 18), suggests that while intention is necessary, enabling conditions (training, data infrastructure, financial support) are essential to translate intention into sustained use. This supports the argument that interventions must address both motivational and structural dimensions to close the intention–behaviour gap.

By triangulating the results of the different section of the study, this research provides a robust and nuanced understanding of adoption determinants, resulting in a combination of psychological factors (attitude, perceived behavioural control), social influences (norms, membership), and systemic enablers (support services, data infrastructures).

Barriers such as lack of technical support and low awareness translate into lower perceived control, while drivers such as economic benefits and regulatory pressure translate into more favourable attitudes.

In addition, the relatively modest weight of norms suggests that there is untapped potential in leveraging peer influence and collective learning to foster behavioural change. At the same time, the strong effect of attitude and control indicates that increasing perceived benefits and lowering complexity remain the most effective levers.

Interestingly, stakeholders perceived data sharing mainly as an opportunity rather than a risk, contrasting with parts of the international literature that emphasise data privacy concerns

(Sullivan et al., 2024). This divergence may reflect the relatively early stage of digitalisation in Italy: when adoption levels are low, opportunities may outweigh perceived risks, but these perceptions could shift as adoption becomes more widespread.

Overall, this study supports the conceptualisation of digitalisation as a systemic transition, where individual attitudes, social norms, and enabling infrastructures interact. Failing to address one of these dimensions may slow down adoption, whereas coordinated interventions such as enabling environments, supportive networks, and effective governance can accelerate behavioural change, translating potential into practice.

Ultimately, this research confirms the validity of the Theory of Planned Behavior (Ajzen, 1991) as a robust framework for explaining behavioural intention in the context of digital technology adoption. The strong effects of attitude and perceived behavioural control validate their central role and justify the continued use of TPB in this field. The finding that intention significantly predicts adoption behaviour further supports TPB's assumption that intention is the proximal determinant of behaviour.

However, it is also revealed that TPB has limitations when applied in isolation, resulting insufficient to fully capture the complexity of adoption processes in agriculture. Indeed, by integrating technical support, membership, and climate change perception, the extended model significantly increases explanatory power. This supports calls from previous authors (McGrath et al., 2023; Shang et al., 2021) for multi-level models that go beyond individual psychology and incorporate contextual and systemic determinants.

In supplement, the indirect effect of membership provides empirical evidence that meso-level factors, such as cooperatives, producer organisations, and advisory services, affect behavioural intention through both social and control-related dimension. This expands the theoretical understanding of how collective action influences innovation diffusion and bridges behavioural theories with network and innovation systems literature (e.g. living labs).

5. Conclusion

This dissertation set out to investigate the determinants of digital technology adoption among Italian farmers, addressing the knowledge gaps identified in the general and scoping literature reviews. The research was motivated by the observation that, despite the potential benefits of digitalisation for productivity and sustainability, adoption rates remain heterogeneous and below expectations in many contexts.

Accordingly, the study aimed to (i) map the main technology adoption factors and theoretical frameworks in the literature, (ii) explore the systemic dimension of agricultural adoption process, (iii) elicit the perspectives of Italian stakeholders on technology adoption barriers and drivers, and (iv) empirically test an extended behavioural model based on the Theory of Planned Behavior (TPB) enriched with systemic constructs.

The general literature review highlighted the dominance of technological and economic factors in agricultural adoption research and revealed the limited operationalisation of systemic and institutional elements. The scoping review further confirmed the methodological fragmentation in studying the systemic domain, finding only a limited part of studies to be theoretically grounded. These reviews jointly established the conceptual basis for extending behavioural models with systemic variables.

The qualitative stakeholder study offered granular insights into Italian barriers and drivers to technology adoption, confirming the relevance of systemic enablers such as technical support, interoperability, and cooperation along the supply chain. Italian stakeholders stressed that economic considerations remain a major driver but that the lack of skills, advisory services, and coherent incentives are key barriers. These findings informed the design of the quantitative model, ensuring that it reflected farmers' real decision context.

Finally, the quantitative analysis provided robust empirical evidence that attitude and perceived behavioural control are the strongest predictors of intention, while subjective norms did not exert a statistically significant effect. As the main novelties, technical support emerged as a crucial systemic determinant, membership influenced intention indirectly primarily through subjective norms, with only marginal mediation via perceived behavioural control, and climate change risk perception did not show a significant effect on adoption intention. The intention/adoption path was significant for both technology ownership and use, validating the predictive power of the TPB model. Among socio-demographic characteristics, only farm size showed a small but significant positive effect, with larger farms more likely to intend adoption.

Together, these results confirm that digitalisation is a socio-technical transition process, where individual motivation, social dynamics, and enabling conditions must align for adoption to occur.

As the main theoretical contributions, this research contributes to the advancement of adoption theory by confirming the explanatory power of the TPB model in agricultural sector and demonstrating the value of extending it with systemic constructs. By integrating variables such as technical support, membership, and climate change perception, the study highlights how external enablers complement individual cognitive drivers, offering a more comprehensive model of behaviour.

Empirically, this dissertation provides one of the first integrated analyses of digital technology adoption among Italian farmers using a mixed-method design. It delivers context-specific evidence on key barriers (e.g., lack of advisory services, interoperability issues) and drivers (e.g., perceived benefits, regulatory compliance, supply chain collaboration), offering a valuable reference point for future comparative studies.

From a methodological perspective, this research adopted a sequential multi-stage design that combined two complementary reviews withqualitative stakeholder investigatione and a quantitative PLS-SEM analysis.This design strengthens the robustness of the findings and allows for the quantification of relationships that were previously explored only descriptively, thereby contributing to a more comprehensive and evidence-based understanding of digital technology adoption.

Digitalisation is widely recognised as a key lever for the transformation of agri-food systems towards greater sustainability, efficiency, and resilience. This dissertation demonstrates that unleashing this potential requires addressing not only farmers' attitudes and capacities but also the systemic conditions that enable adoption, including support services, data governance, and collective action mechanisms.

By bridging literature analysis, stakeholder insights, and empirical modelling, the study offers a nuanced understanding of adoption dynamics and provides actionable recommendations for policy makers, cooperatives, and technology providers.

5.2. Policy implications

From a practical standpoint, the findings indicate that policy interventions in Italy should move beyond a purchase-centred approach and instead target the conditions that enable effective and sustained use of digital technologies. In line with the observed discrepancy between ownership and utilisation, support schemes should progressively reward continuous adoption indicators and verifiable performance metrics, rather than subsidising acquisition alone. This would help close the intention–behaviour gap by coupling motivation with the systemic conditions required for durable implementation.

Given the strong role of perceived behavioural control and the significant contribution of technical support to adoption intention, strengthening advisory capacity emerges as a priority. Policies should promote structured training programmes, demonstration networks, and continuous support services delivered through trusted local intermediaries. Advisory initiatives should be designed not only to transfer knowledge, but also to reduce perceived complexity, improve implementation confidence, and make benefits visible under real farm conditions.

Italian stakeholders also highlighted data fragmentation and incompatibility as major barriers; therefore, digitalisation policies should explicitly address data governance and interoperability. This implies supporting open standards, shared protocols, and interface compatibility across tools, as well as promoting institutional arrangements that facilitate secure data sharing for benchmarking and decision support. In parallel, policy frameworks should encourage solutions that lower transaction costs for data integration, since the adoption of data-intensive technologies is unlikely to scale where data remain siloed across providers and platforms.

As organisational membership operates primarily through social and enabling mechanisms, policies should treat cooperatives, producer organisations, and supply-chain actors as innovation intermediaries capable of amplifying peer learning, trust, and shared problem-solving. Instruments that strengthen bridging actors—conceived as entities able to connect farmers across scales to advisory services, innovation networks, and market opportunities—can reduce structural entry barriers and broaden participation. At the same time, the differentiated role of membership types suggests an equity-relevant implication: where contract-based supply-chain schemes are more accessible to medium and large farms, targeted measures are needed to lower entry barriers for smaller farms (e.g., collective participation mechanisms, shared service models, or data-cooperative arrangements that enable indirect compliance and shared investments).

The results further imply that policies should incentivise demand-driven technology development and dissemination strategies grounded in farm-level constraints and oriented to usability. Aligning technology supply with farmers' operational needs (time constraints, skills, compatibility with existing machinery and routines) can reduce learning burdens and strengthen perceived behavioural control. In this perspective, technology providers should be encouraged—through procurement criteria, innovation calls, or standard-setting—to invest in interoperability, usability, and clear value propositions, rather than expanding portfolios in ways that increase fragmentation.

Collectively, these measures reflect the core message emerging from the thesis: adoption is not only an individual decision but a socio-technical outcome, and scaling digitalisation requires policy mixes that jointly address behavioural drivers and the systemic conditions that make sustained use feasible.

5.3. Limitations and future research

Several limitations should be acknowledged. Regarding geographical scope, this research deliberately focused on developed countries and excluded smallholder contexts, consistent with the analytical framework and research objectives defined in Chapters 1 and 2. This focus ensured comparability with the empirical analysis conducted in the Italian context and avoided the confounding effects that could arise from including structurally different farming systems. This scope condition ensured coherence with the analytical framework and the Italian empirical setting, but it limits generalisability to contexts characterised by comparable structural and institutional conditions.

The qualitative study, by design, cannot be fully generalised and may suffer from selection bias and moderator effects, despite the use of methodological triangulation and saturation criteria. Importantly, all key stakeholder categories along the agri-food value chain were represented, which strengthens the comprehensiveness of the findings; however, there is always the possibility that additional stakeholder groups were not captured. Therefore, future research should verify the exhaustiveness of stakeholder categories by including any additional stakeholder groups that may have been overlooked, to ensure an even broader representation. Moreover, as noted in the published study, qualitative techniques such as focus groups and semi-structured interviews may be affected by group dynamics (e.g., dominant participants, reticence) and time-intensive data collection, which can limit replicability. These risks were mitigated in this research by using an experienced moderator and achieving theoretical saturation.

The quantitative survey is cross-sectional and based on self-reported data, which may introduce response bias. Moreover, the survey relied on a non-probability convenience sampling strategy disseminated through online social networks. This may generate self-selection bias, as participation is more likely among farmers who are digitally connected, more interested in innovation, or already closer to the topic of digitalisation. Consistent with this, the achieved sample overrepresents younger respondents and larger farms, which may inflate descriptive estimates of adoption and intention and may reduce the visibility of constraints that are more salient in smaller and older farms (e.g., limited capital, skills, time, and access to specialised support). Therefore, results should primarily be interpreted as associations holding for this online convenience sample rather than as population-level estimates. Future research should strengthen external validity through probability-based or stratified sampling frames, targeted recruitment of underrepresented groups, and—where population margins are available—post-stratification weighting and robustness checks across age and size strata.

In addition, future development could extend the present theoretical model specification by modelling farmers' baseline digital familiarity more explicitly, for example by allowing technological knowledge (Know) to predict not only intention but also upstream TPB constructs (e.g., attitude and/or perceived behavioural control), and by testing moderated effects (e.g., high- vs low-knowledge groups) to assess whether the behavioural mechanisms differ by digital literacy.

Although the technologically neutral approach adopted in this study increases generalisability across tools and production systems, the context-specific nature of adoption decisions means that results cannot be fully generalised to all settings. Future research should therefore complement these findings with longitudinal designs and context-specific case studies to capture adoption dynamics over time, investigate the intention–behaviour gap, and test whether the observed relationships hold across diverse production systems and regional settings within developed economies.

Nevertheless, the combination of three complementary methods increase the robustness and credibility of the overall findings through triangulation, strengthen internal validity while external validity remains conditioned by the non-probability survey design.

Given the technologically neutral approach of this research, further studies could disaggregate digital technologies into categories (e.g., hardware, software, DSS, automation) to determine whether different adoption determinants apply to each category, thereby enabling more targeted recommendations and tailored policy instruments.

Future studies should incorporate richer baseline controls capturing farmers' starting point—such as prior exposure to digital tools, initial technology endowment, and previous training/experience—and include them as covariates (or moderators) within the behavioural model. However, our descriptive evidence on ownership versus use suggests that possessing a technology does not necessarily translate into effective utilisation, indicating that analyses focusing solely on endowment may miss the core behavioural mechanism. In line with perceived-benefit logics emphasised in technology acceptance research (e.g., Davis' usefulness-based perspective), greater explanatory leverage may come from modelling perceived benefits and usability beliefs rather than mere availability. Methodologically, this also implies that future work should clearly distinguish non-adopters from partial adopters (owners-non-users) and active users, or alternatively estimate belief–intention mechanisms on a restricted sample of non-adopters, where intention formation is not mechanically confounded by prior adoption.

Beyond addressing the limitations above, future studies should also evaluate the effectiveness of policy and advisory instruments through experimental or quasi-experimental designs. This is particularly relevant because the scoping review revealed that most existing studies are descriptive and focus on correlations rather than causal effects, leaving limited evidence on which interventions truly drive adoption and increase usage intensity. Rigorous impact assessments of training programmes, data cooperatives, and performance-based subsidies would therefore provide policymakers with actionable evidence on the most effective levers for promoting digitalisation.

The role of networks, as suggested by the significant membership effects observed in the quantitative study, could be further explored using social network analysis (Ramirez, 2013) or innovation system mapping to identify key influencers and bottlenecks. Participatory approaches such as living labs or co-design experiments could be tested as interventions to strengthen cooperation and enhance perceived behavioural control, thereby accelerating diffusion.

Finally, cross-country comparative studies within developed economies would be valuable to examine how institutional contexts, market structures, and cultural factors shape adoption behaviour. Such research would allow for the validation (or contextualisation) of the findings in comparable settings and contribute to the development of a more generalisable yet context-sensitive theory of digital agriculture adoption, supporting both academic advancement and evidence-based policy design.

AI use disclosure

Generative AI tools were used exclusively for editorial assistance such as language refinement and improving clarity of expression. The author reviewed and approved all included information and retains full responsibility for its accuracy and integrity.

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