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Economic and policy analysis of technology uptake for the smart management of agricultural systems

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INTRODUCTION

This special issue of Bio-based and Applied Economics "Economic and policy analysis of technology uptake for the smart management of agricultural systems" stems from the growing diffusion of innovative digital technologies as strategic solutions for the development of the agricultural sector.

Agriculture is undergoing a profound transformation thanks to the integration of new technologies (Vishnoi and Goel, 2024; Aijaz et al., 2025), with a view to the sustainable development of the sector (Norman and MacDonald, 2004; Nica et al., 2025). The combined economic and environmental benefits of technology adoption in agriculture are widely recognized in the literature (Giorgio et al., 2024; Papadopoulos et al., 2025). To illustrate, technologies in agriculture help address current interconnected challenges related to productivity, cost reduction, agri-food safety, natural resource conservation, animal welfare, worker safety, and, more generally, the achievement of sustainable development goals (Castillo-Díaz et al., 2025; Finger, 2023; Basso and Antle, 2020; Musa and Basir, 2022; Sridhar et al., 2023). In this context, technological innovations have enabled significant improvement of various agricultural processes through the introduction of different tools, such as the Internet of Things (IoT), sensors, robotics, drones, blockchain, and artificial intelligence (Sharma and Shivandu, 2024). As discussed by Arraigada and Mac Clay (2025), these tools can either complement traditional technologies (e.g., IoT sensors connected to conventional irrigation systems) or substitute them (e.g., spraying drones replacing a traditional sprayer).

The diffusion of innovative digital tools in agriculture is growing (Shang et al., 2021), but their take up still varies significantly across countries, farm types, and production systems (Eastwood et al., 2019; Rose and Chilvers, 2018; Shepherd et al., 2020). This uneven pattern highlights the need to understand the mechanisms underlying the adoption of these technologies and suggests that digital transformation in agriculture is not just

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about technology, but also depends on social structures, institutions, and interactions between networks and governance systems (Roberts et al., 2017; Jia, 2021), as well as farmers' personal attitudes and traits (Deißler et al., 2022).

This special issue contributes to the ongoing debate on how digitalization is reshaping agriculture. Combining behavioral theories, such as the theory of planned behavior (Ajzen, 1991), the technology acceptance model (Davis, 1989), and the unified theory of technology acceptance and use (Venkatesh et al., 2012), with economic and policy analyses, the articles examine in detail the factors that help or hinder farmers in adopting new technologies (Maesano et al., 2025; Cozzi et al., 2025; Moussaoui et al., 2025).

PRESENTATION OF THE SPECIAL ISSUE

The articles collected in this special issue aim to offer a broad and multifaceted view of the dynamics linked to the diffusion of innovative digital technologies in the agricultural sector, considering the behavioral, economic, and political dimensions that influence the intention to adopt them.

Kühnemund and Recke (2025), drawing on the Technology Acceptance Model (TAM) framework, investigate the determinants that drive German pig farmers to introduce AI-based camera systems into livestock production. Their findings indicate that perceived ease of use, openness to innovation, and individual innovativeness are the main factors influencing adoption intention. Concerns about data ownership and privacy, however, play a lesser role in driving behavior. Overall, the authors argue that farmers place significant importance on the reliability and functionality of technology. However, trust and transparency are essential determinants of technology adoption. These findings underscore the importance of user-centered design and clear communication regarding how intelligent technologies are implemented in practice.

Cozzi et al. (2025) conduct a study in the Italian horticultural sector, to analyze the adoption of water-smart technologies. Based on data from a survey of 251 farmers in Italy, using an extended TAM3 framework, the authors find that perceived usefulness and social norms strongly influence adoption intentions. The results also show that ease of use is less influential in driving intentions. Their analysis highlights how social interaction and perceived benefits outweigh usability or socioeconomic characteristics in shaping farmers' behavior. From this perspective, the findings suggest that participatory and peer-learning environments can serve as effective channels to accelerate the diffusion of innovation. The findings are consistent with those of Sabbagh and Gutierrez (2025) and Kühnemund and Recke (2025), both of which emphasize the key role of social capital in linking technological potential to actual behavioral change.

Sabbagh and Gutierrez (2025) extend the Unified Theory of Acceptance and Use of Technology framework to analyze the adoption of Agriculture 4.0. The authors identify the main determinants of adoption by comparing marginal and non-marginal areas. Their findings reveal that facilitating conditions, such as access to infrastructure and technical support, and social influence are the main predictors of adoption. Furthermore, according to the study's findings, perceived performance risks have been shown to be barriers to adoption. The authors conclude that adoption intentions depend not only on individual motivation, but also on social and territorial structures that enable knowledge exchange and reduce perceived risk. These findings echo previous work on the rural digital divide, highlighting the need for context-specific policies (Rose and Chilvers, 2018; Eastwood et al., 2019).

Timpanaro et al. (2025) contribute to the literature debate by analyzing the methods of introducing digital tools and their effects in Sicilian citrus farming. Using a Living Lab approach, the authors demonstrate that digital technologies can increase yield per hectare, improve profitability, and enhance water efficiency on citrus farms. Their findings also indicate that participatory innovation processes promote knowledge exchange and collaboration, helping to reduce farmers' resistance to change. The study highlights the need for targeted training and institutional support to ensure that digitalization is effective and inclusive. This participatory perspective resonates with the call for innovation ecosystems that integrate technology into local socioeconomic contexts and sustainability goals.

Maesano et al. (2025) examine the factors influencing Italian consumers' intentions to purchase organic pasta traced using blockchain technology. Extending the Theory of Planned Behavior (TPB) framework (Ajzen, 1991), the authors assess the potential of blockchain in preventing and detecting food fraud. Their findings suggest that subjective norms, perceived behavioral control, and attitudes toward technology are the main predictors of purchase intention, while trust in traditional quality certifications plays a limited role. Therefore, consumers place greater trust in digital traceability tools than in conventional certification systems. However, from a consumer perspective, uncertainty remains about the practical benefits of these technologies, highlighting the need for a credible and transparent environment in which innovation provides clear added value.

Pacciani et al. (2025) evaluate digitalization levels, perceived benefits, needs, and barriers on a sample of 1,248 Italian farms. The results show that monitoring systems and connected machinery are the most used technologies. In addition, efficiency gains in farm and production management, improved operational control, and perceived benefits are key drivers of adoption, while financial and structural limitations remain significant obstacles. The authors call for coordinated policy measures to support the digital transition, combining advisory services, investment in infrastructure, and human capital development. Their conclusions are consistent with those of Sabbagh and Gutierrez (2025) and Timpanaro et al. (2025), who also emphasize the importance of governance coordination, training, and connectivity in promoting technology diffusion.

Moussaoui et al. (2025) employ a mixed-methods design, combining surveys and in-depth interviews to gather stakeholder perspectives on smart agriculture technologies and their policy integration. The results of the study show a broad agreement on the potential of technologies to improve agricultural efficiency, sustainability, and productivity; nonetheless, it also identifies persistent barriers, including high upfront costs and limited technical expertise. The authors highlight the need for financial incentives, capacity-building initiatives, and stronger infrastructure to encourage adoption. The conclusion of this study supports adaptive, multi-level governance frameworks that link top-down policy design with bottom-up innovation processes to ensure greater policy coherence. In line with Pacciani et al. (2025), their findings reinforce the view that digital transformation depends as much on systemic governance reform as on technological progress.

Finally, Arraigada and Mac Clay (2025) expands the geographical scope with an exploratory study of digital agriculture (DA) start-ups in Argentina, providing comparative insights from the Global South. The paper discusses the interactions between the established agricultural input industry and 114 DA start-ups based on two technological dimensions: embodied/disembodied technologies and complementary/substitutive. Overall, the analysis shows that most of the solutions developed by Argentine start-ups tend to be complementary to the existing technological packages, and this may represent an opportunity for dominant firms to strengthen their position either by acquiring or investing in early-stage start-ups to incorporate those solutions into their own technological platforms.

CROSS-CUTTING INSIGHTS AND POLICY IMPLICATIONS

This special issue offers different perspectives on the dynamics of technology adoption and the governance of digital transformation in agriculture. The evidence confirms that technology adoption is not merely a technical or economic process (though these aspects are very important), but it is a socio-institutional transition, that depends on mental constructs, social norms, and collective learning mechanisms, and is strongly influenced by the external conditions in which innovations are embedded. Behavioral models indicate that perceived usefulness and social influence are the main determinants of farmers' acceptance of innovations. Conversely, perceived risk, high costs, and institutional uncertainty remain the main barriers.

From a policy perspective, the findings highlight that monetary incentives alone will not ensure a successful digital transition unless they are part of coherent and flexible governance arrangements that align public and private resources, promote interoperability, and leverage synergies within the sector (Wolfert et al., 2017; Klerkx et al., 2019; Viaggi, 2019). The articles in this special issue suggest that effective strategies must combine investment with the development of digital infrastructure and educational programs to build long-term innovation capacity. More generally, the integration of behavioral and economic policy analysis in these articles demonstrates how interdisciplinary science can inform evidence-based solutions to ensure the deployment of smart technologies in the context of resilient agri-food systems.

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This Special Issue also saw the participation of our colleague Maurizio Canavari, who passed away prematurely at the beginning of 2025, far too soon. He was a curious, generous, and committed scholar, deeply engaged in the fields of agri-food economics and consumer behavior. His collaborative spirit enriched all those who had the privilege to work with him. Maurizio

contributed to the conception, design, and realization of one of the studies included in this Special Issue, namely Cozzi et al. (2025). He leaves an indelible memory among his colleagues and students.

All guest editors contributed equally to the conception and writing of this editorial.

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Intention to use AI-Based Camera Systems in German Pig Farming: An extended technology acceptance model

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Abstract. This study explores the factors influencing German pig farmers' intention to use (ITU) AI-based camera systems in livestock farming. This research utilized an extended Technology Acceptance Model. Data from 185 farmers were analyzed through structural equation modeling, revealing that ease of use (β=0.276), innovation tolerance (β=0.398) and personal innovativeness (β=0.101) notably impact ITU. Concerns over data ownership and transparency showed limited effects, and perceived job relevance (β=0.355) enhanced acceptance. Expected transparency of AI camera systems had strong influence on perceived ease of use (β=0.419). A gradual integration of the factors showed that perceived usefulness has a strong influence on ITU but is superimposed by the factor job relevance in the modelling process. With an R2 of 0.749, the model has high explanatory and predictive power. These insights underscore the importance of user-centric design and transparency in AI technology deployment in agriculture. Although the ITU AI camera systems in pig farming depends on its ease of use and transparency, it also depends on the personal characteristics.

Keywords: AI, surveillance, precision livestock farming, technology acceptance.

1. INTRODUCTION

Pig farmers face major challenges in the production and processing of animals. On the one hand, legal requirements for animal health and animal protection in Germany increased (German Federal Ministry of Food and Agriculture, 2024), e.g. ban on tail docking and requirements for defined husbandry types. On the other hand, pig farmers are faced with societal demands for production like animal rights values (Albernaz-Gonçalves et al., 2021). For this reason, the integration of artificial intelligence (AI) into the processes associated with pig farming is needed to improve modern agriculture. Therefore, an increasing number of animal behavior monitoring technologies have been developed over the last decade. Many of these solutions focus on the combination of visual recordings and artificial intelligence interpretation. In pig farming, these innovations range from live weight detection (Wongsriworaphon et al., 2015) and growth (Condotta et al.,

2018) to behavioral detection (Nasirahmadi et al., 2019) and early disease detection (Fernández-Carrión et al., 2020). As a result, AI technologies can not only increase productivity but also improve overall animal welfare through early disease detection and prevention.

However, the adoption of AI systems and the use of intelligent systems in animal husbandry are less common than that of other technologies on farms in Germany (Rohleder et al., 2020). The aim of our study is to investigate the factors that determine the intention to use AI camera systems in pig farming. In the context of livestock farming, cluster analyses have identified heterogeneity in attitudes toward the agricultural technologies used (Schukat & Heise, 2021). In addition, various studies on the intention to use (ITU) farming technologies have reached different conclusions. Michels, Bonke, et al. (2020) investigated factors that influence farmers' use of smartphone apps for crop protection. Their analyses revealed that performance expectancy and social norms were among the determining factors for the ITU. In contrast, Mohr and Kühl (2021) investigated the acceptance of AI technologies in agriculture in general and reported that previous factors have no influence on the intention to use them. In their study, for example, the perceived ease of use and the expectation of property rights over business data were decisive factors influencing the intention to use. This finding indicates the importance of analyzing the factors that determine the intended use of specific technologies and target groups. An established method for analyzing the usage intentions of potential target groups is the technology acceptance model (TAM) from Davis (1985). The TAM and various extensions, as well as models based on the original model, are precise means of determining the factors influencing the intention to use and predicting possible utilization (Davis & Granić, 2024). The model has also been applied to agricultural technologies in different studies (Alambaigi & Ahangari, 2016; Mohr & Kühl, 2021; Thomas et al., 2023). Besides intentional models using the TAM there are different other models used in the case of agricultural technologies. For example, the theory of planned behavior (TPB) (Ajzen, 1991) have often been used in the context of the implementation of new technologies in the rural economy. Sok et al. (2021) identified several articles in the field of animal husbandry that successfully applied to the TPB. In German agriculture this method was applied in study investigates the adoption of mixed cropping (Michels, Bonke, et al., 2020). In addition, a small number of researchers have examined technologies in agriculture from the perspective of stage-based models (Block et al., 2023; Lemken et al., 2017), such as the Transtheoretical Model of Behavioral Change (TTMC) (Prochaska & Velicer, 1997). This concept can be used to predict behavioral change and has its origins in the health sciences. Applying the model to adaptation is difficult at this stage because similar technologies are not yet available, or are limited, and understanding of the potential benefits can be very narrow. Despite the variety of approaches aiming to understand the use intentions of potential target groups, a TAM-based study is an appropriate choice, especially for technologies in the early stages of development and with low market penetration (Davis & Granić, 2024). Findings from TAM and new extensions provide valuable insights for potential technology users and help developers and policymakers set the right course for the adaptation of useful technologies.

The differentiation of the technology in question, especially in the field of AI, is necessary to define the research object and draw specific conclusions. In general, AI can be difficult to grasp with respect to the selected target group and application, as there are different perceptions of what AI is and can do. It is therefore useful to design research on the acceptance of technologies according to the object of investigation. Another reason to analyze this special issue related to AI technology is that both camera systems and AI that use image data are sensitive cases for potential users (Saheb, 2023). Since AI-based camera systems are relatively new and the use of this technology in the context of German livestock farming is low, this study on intention to use is essentially a theoretical ex ante model (Pierpaoli et al., 2013). Against this background, this study analyzes the influence of theoretically derived factors on the utilization intentions of German pig farmers. In addition, the research should help technology developers to adapt their systems to enable better market integration. Insights into the relevant characteristics that influence adoption intentions can help to inform farmers about AI camera systems in a targeted way. The findings should also serve to identify potential barriers to adaptation and provide an opportunity for developers and policy makers to take these into account. We use an extended technology acceptance model, which is explained and justified in more detail in the methods section.

2. THEORETICAL FRAMEWORK

This investigation uses the TAM to analyze the potential adoption behavior of German pig farmers and to explain the intention to use this technology in terms of acceptance (Useche et al., 2013). In the context of the technology and the potential users (farmers), we expand this model to the context of pig farmers and the usage of

AI camera surveillance, as shown in the following chapter The TAM is based on two factors, perceived usefulness (PU) and perceived ease of use (PEOU), which are decisive for the possible acceptance of new technologies by potential users (Davis, 1989). The PU indicates the degree to which a system improves work performance and, according to its founder Davis, is a strong influencing factor on the use of technology (Davis, 1989). The PEOU indicates how difficult or simple potential users consider learning and using a system or technology to be (Davis, 1989). In the original model, the two factors act as explanatory and predictive variables for the intention to use a new technology. The model in our analysis showed a lack of explanatory power which substantiated the contextual extension. Figure 1 illustrates the original TAM framework.

Contextual model extension

In addition to the PU and the PEOU, many other factors affect users' intention to use new technologies (Pierpaoli et al., 2013). With the aim of identifying these factors, various extensions of the TAM have been made over time and embedded in other concepts to generate independent models that explain the intention to use technologies (Davis & Granić, 2024). In a systematic overview, Granić (2024) presented a total of 17 different models that analyze technology adoption at the individual level. These include, for example, the extended unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2012) and innovation diffusion theory (IDT) (Rogers, 1975). This resulted in a wide range of possible predictors for the intention to use technologies, whereby different aspects can be categorized in relation to the users, technology, tasks and social factors (Davis & Granić, 2024). Instead of applying one of the existing models to AI-based camera systems, it appears that the special nature of the technology and the task, as well as the users, make an extension necessary that considers these special aspects. In the present research, the combination of surveillance technology and the use of AI, in particular, plays a decisive role in this type of expansion.

A literature search in the Scopus and SpringerLink databases during the conception phase of the study led to the factors explained below and, finally, to our extended TAM. As part of the modeling process, we assigned the individual constructs to the categories of farmer aspects, technological aspects and social aspects.

Farmers' aspects

Innovation tolerance (IT) is a combination of risk attitudes and the expectation of future relevance from the user's perspective. These factors can be well integrated into a behavioral model such as the TAM (Montes de Oca Munguia et al., 2021). It is known from the literature that risk aversion has a negative effect on technology adoption (Abadi Ghadim & Pannell, 1997). Conversely, Seibert et al. (2021) showed in their systematic literature review the positive effect of the willingness to take risks on the intention to use new technologies. A decision under uncertainty involves, in the context of technology adoption, the derivation of the value of the technology in the future. Innovators recognize the value of the technology and the future benefits that its use and rapid adaptation offer. They are convinced that utilization will be important in the future to benefit from

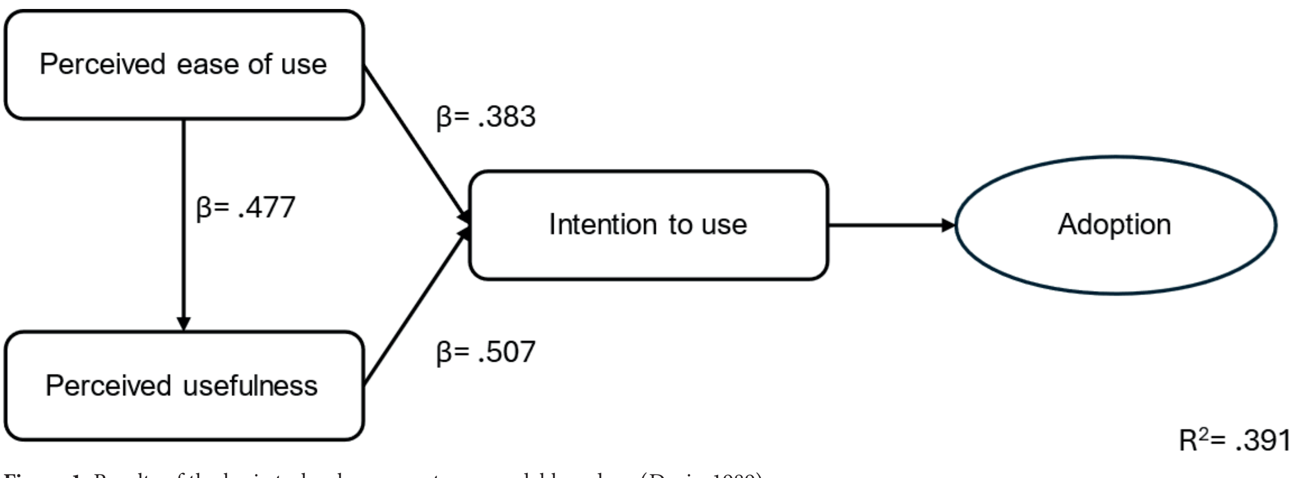

Figure 1. Results of the basic technology acceptance model based on (Davis, 1989).

adoption (Rogers, 2003). Those who see high potential in new technologies for the future are prepared to use the technology now. This study assumes that the combination of self-perceived risk behavior and the assessment of the importance of using technology in the future is decisive for the intention to use it.

Personal innovativeness (PI) extends models of technology acceptance by considering individual perceptions and beliefs (Agarwal & Prasad, 1998). People are described as innovative when they adopt new innovations at an early stage (Rogers & Shiemaker, 1971). A study on precision agriculture technologies revealed significant correlations between technology acceptance and PI as well as a moderating effect on the ITU by influencing the PEOU (Aubert et al., 2012). In her study on the adoption of virtual reality simulations, Fagan et al. (2012) reported a significant interaction between PI and PEOU. In the context of AI and agriculture, Mohr and Kühl (2021) showed the influence of the PI on the PEOU.

Job relevance (JR) describes the extent to which AI-based camera systems are relevant for daily tasks with animals from the user's perspective. Farmers are more likely to use an information system if they perceive that the information it conveys is relevant to their job (Venkatesh & Davis, 2000). In the context of German livestock farmers, the pressure to use technologies to improve their jobs is a factor underlying the behavioral acceptance of farmers. In addition to the direct influence of JR on the intention to use new technologies, (agricultural) studies have highlighted the significant effect of this variable on PU (Marangunić & Granić, 2015; Michels et al., 2021).

Technological aspects

The expectation of property rights (PRs) over business data plays an important role in the development of digitalized livestock farming. PR, particularly in the context of AI systems and camera technology, is unclear from a legal perspective (Härtel, 2020). The acceptance of AI-based camera systems is linked to the expectation of ownership and the legal certainty of the data created and used in this context (Härtel, 2020). Another point pertains to the need for AI systems for data-driven learning; for example, camera systems require video and images. Currently, it remains unclear who owns the original data and the data processed by the AI system. In relation to the cultural context, German individuals are critical of issues related to data security, especially with regard to the use of surveillance technology (Kostka et al., 2021; van Heek et al., 2017). A farmer who expects to own the data is assumed to be less willing to use an AI-based camera system.

The perceived risk of data abuse (RI) is a crucial factor for the intention to use new AI technologies. The use of AI and camera technology indicates a type of surveillance. Fundamental changes in the work environment and people's trust in AI often lead to irrational worries in German society even at the individual level – a phenomenon that has been called "German angst" (Nickl, 2014). In their study, Beaudry and Pinsonneault (2010) reported that emotions such as anxiety have negative effects on the intention to use and PU of technology. In terms of surveillance characteristics, the RI has an impact on ITU camera technology (Krempel & Beyerer, 2014). With respect to the combination of AI and surveillance technology (Park & Jones-Jang, 2022), acceptance and even PU and PEOU can be negatively influenced. In terms of the adoption of AI technologies in a professional context, Dumbach et al. (2021) identified data protection as the most challenging barrier with respect to AI technology.

With respect to surveillance systems, the expected data transparency (TR) of the processed data and the operation of the system itself are important factors in the acceptance of camera technology (Krempel & Beyerer, 2014). It is difficult or even impossible to understand all aspects of AI systems, even when they are fully transparent. This situation represents a black box that may hinder the development of trust (Dam et al., 2018). However, transparency is a major driver of trust, which determines people's willingness to accept strategic uncertainty (Poursabzi-Sangdeh et al., 2018; Schmidt et al., 2020; Zhao et al., 2019). A study by Wanner et al. (2022) concluded that transparency on AI-based camera systems affects the PU and PEOU (Wanner et al., 2022). A transparent system is easier to understand; thus, the PEOU and PU increase because people have more knowledge about the system.

Social aspects

Perceived social norm (PS) is based on perceived social pressures, personal feelings of moral obligation and the responsibility to engage in or refuse to engage in a specific behavior (Gorsuch & Ortberg, 1983). The expectations of behavior created by social pressure influence the intention and actual decision to behave in a certain way (Ajzen, 1991). German consumers assess their knowledge about agriculture as rather low (Heinke et al., 2017). However, even without sufficient knowledge, many consumers have a critical view of livestock production (Heinke et al., 2017). In the past, technological development in agriculture has been viewed critically by the population (Gupta et al., 2012; Pfeiffer et al., 2021). With respect to animal production, the public opinion of technological development has been accompanied by a negative comparison with natural outdoor husbandry (Cardoso et al., 2016; Weinrich et al., 2014). The expected view of society for AI-based camera systems therefore seems relevant, as tasks are transferred from farmers and the process of animal husbandry is autonomized. However, meat consumers have expressed a preference for innovation as a solution to potential problems in animal husbandry (Schulze et al., 2023). These findings highlight the ambivalent attitudes of the public.

Table 1 summarizes the factors included in our extended TAM.

After the potential explanatory factors were identified, the individual structures were hypothesized in the structural model. Appendix 1 shows the list of individual hypotheses. Figure 2 shows the hypothesized effect of each factor on the intention of potential users to adopt the technology.

3. STUDY REGION, DATA COLLECTION AND SAMPLING

The target population of our investigation was pig farmers in Germany, who are decision-makers on their farms. The questionnaire was distributed through an agricultural panel to recruit participants from all federal states of Germany. The members of the panel were recruited throughout Germany via Deutscher Landwirtschaftsverlag, a specialized publishing house for agricultural media, which provides panels for various target groups in the German-speaking area. This approach also ensured that farmers who were not involved in the pig industry were not included in the data collection. The survey was conducted online between January and March 2023. The recruitment resulted in a total sample of 185 participants. Our sample can be considered a convenience sample, which is useful for studies with a pilot character, such as the present study on the ex-ante intention to use a technology (Teddlie & Yu, 2007). The participants were contacted via e-mail and initially informed about the study project. Before beginning the questionnaire, the participants provided informed consent to participate in the study.

The questionnaire (Appendix 2) was divided into different parts. The first part of the questionnaire collected sociodemographic and farm-related information. After the sociodemographic questions, the participants were presented with a description of the AI-based camera systems to provide them with a better understanding of the research object. This description was presented in text form. In the second part, farmers were asked to evaluate several statements pertaining to the extended TAM. Appendix 2 shows the different items, including the questions and descriptive statistics. The survey was administered in German, and the questions were translated into English for this manuscript; however, they were not adapted to the specific cultural context. To assess the statements, the questionnaire used a five-point Likert scale ranging from 1 = do not agree to 5 = fully agree. The questionnaire was pretested by two researchers with different groups of farmers to ensure that all the questions could be understood and interpreted unilaterally. These pretests featured two groups of 15 participants. After the test, the participants were asked about their understanding of the survey and its logic, and adjustments were made if they did not understand the statements or the sociodemographic questions. In addition, the intelligibility of the description of the subject matter was assessed by the test group.

Table 1. Extended TAM constructs.

Category	Factor	Source
Farmers aspects	Innovation tolerance (IT)	Own creation based on (Rogers, 2003; Seibert et al., 2021)
	Personal innovativeness (PI)	(Agarwal & Prasad, 1998; Aubert et al., 2012; Mohr & Kühl, 2021)
	Job relevance (JR)	(Rose et al., 2016; Venkatesh & Davis, 2000)
Technological Aspects	Expectancy of property rights over business data (PR)	Own creation based on (Tiwari & Tiwari, 2020; van Heek et al., 2017)
	Perceived risk of data abuse (RI)	(Krempel & Beyerer, 2014)
	Expected data transparency (TR)	(Krempel & Beyerer, 2014; Wanner et al., 2022)
Social aspects	Perceived social norm (PS)	(Ajzen, 1991; Gorsuch & Ortberg, 1983; Heinke et al., 2017; Mohr & Kühl, 2021; Schulze et al., 2023)

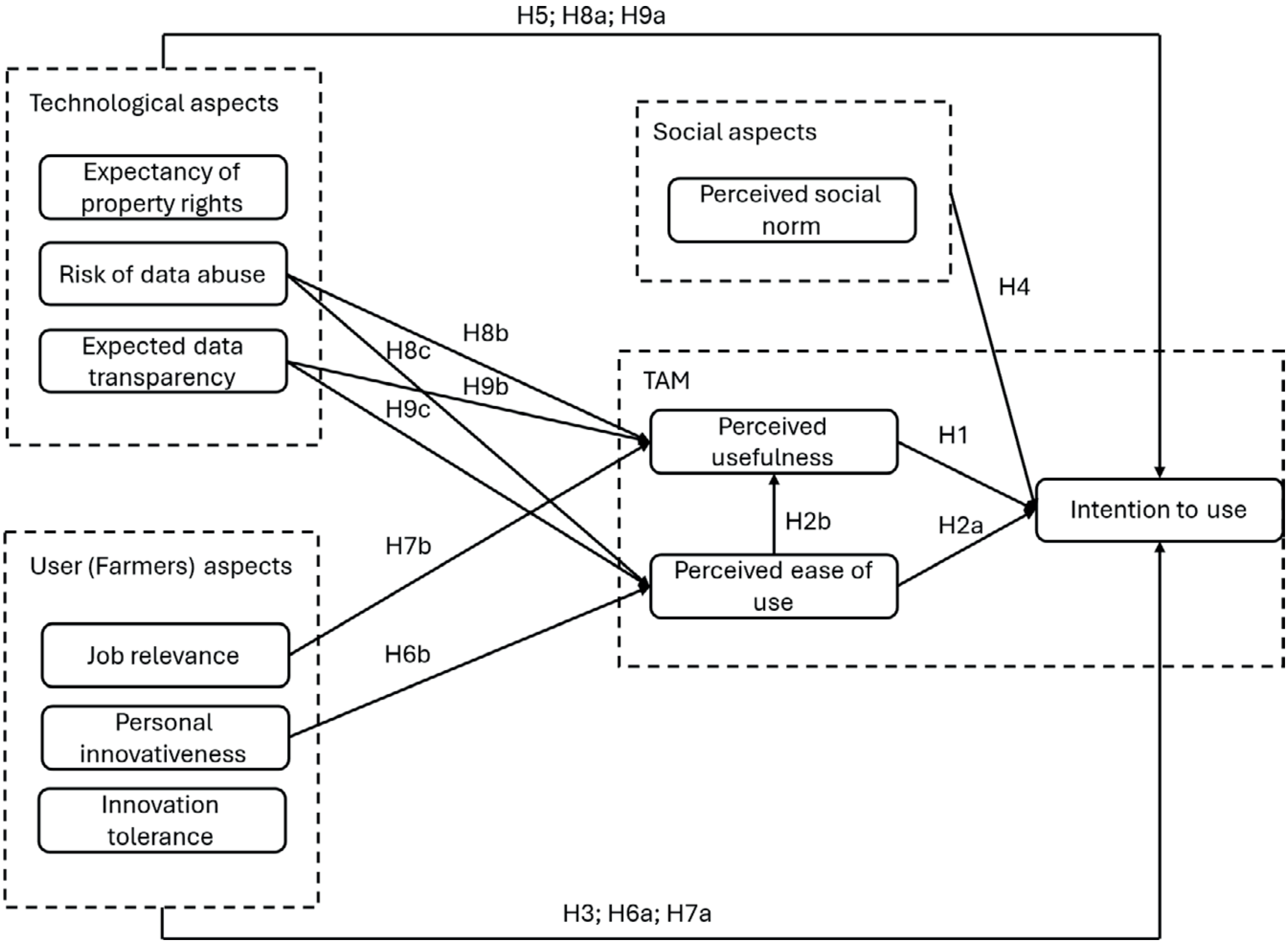

Figure 2. Expanded TAM based on Davis (1989).

4. STATISTICAL ANALYSIS: STRUCTURAL EQUATION MODELING

Structural equation modeling (SEM) is used to model and estimate the relationships among multiple independent and dependent variables concurrently (Hair et al., 2021a). This method is particularly useful when the concepts under consideration are unobservable and are measured indirectly through multiple indicators. This research uses the latest approach developed by Hair et al. (2021a) with the assistance of the R package SEMinR (Hair et al., 2022). In SEM, path models are used to represent the relationships among constructs or latent variables. Latent variables cannot usually be measured directly and are therefore created by indicators or manifest variables. The path model visualizes the relationships among all the constructs and depicts the hypotheses that relate the variables via these paths (Hair et al., 2021a). A partial least squares (PLS) path model consists of two elements. The first element is the structural model, also known as the inner model, which links the constructs. The inner model also represents the hypothesized relationship between the constructs. Second, the path model contains a measurement model or outer model. This model represents the relationships between the constructs and the individual indicators.

Figure 3 shows the exemplary inner and outer models for the latent JR in the context of this investigation. The inner model is shown in the center of the figure. The relationships among the elliptical constructs or latent variables are represented by the connecting arrows. The outer model on the left is a formatively measured construct captured by the indicators (JR1, JR2, and JR3). The outer model on the right shows a reflectively measured construct, in this case, the dependent variable ITU. In addition to the indicators used to measure the construct, the error terms for the manifest variables are recorded. These error terms represent the unexplained variance when the path model is estimated.

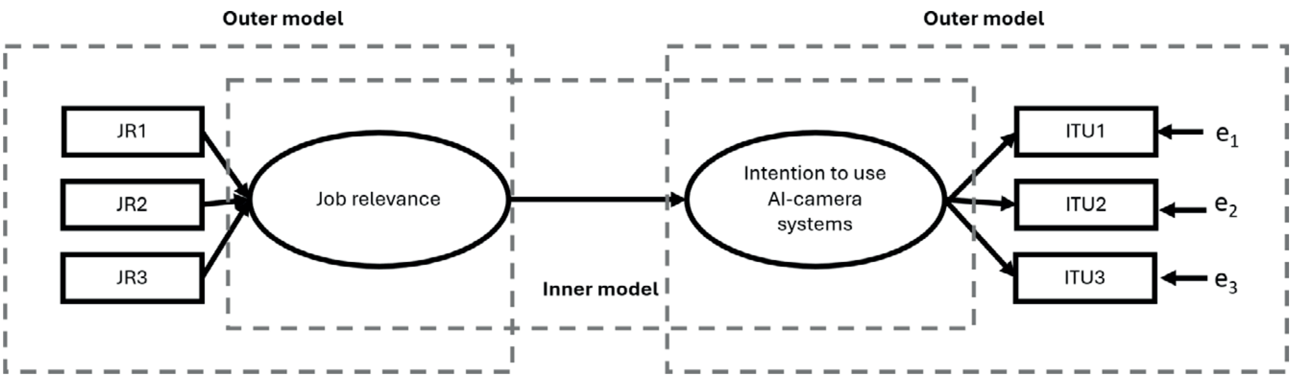

Figure 3. Structural equation model (Hair et al., 2022).

However, this description applies only to the manifest variables. In contrast, the formative variables, in which context the relationship leads from the indicator to the construct, have no error terms (Sarstedt et al., 2016).

Minimum sample planning

In general, PLS-SEM is applicable if the sample contains ten times as many participants as independent variables (Thompson et al., 1995). However, concerns have been expressed about the simple application of this "ten times" rule in the case of complex structural models. An alternative procedure is represented by the inverse square root method (Kock & Hadaya, 2018), which is used to calculate the probability that the path coefficient and its standard error are greater than the critical value for a predetermined significance level (Hair et al., 2021a). Therefore, the minimum sample size (Kock & Hadaya, 2018) is obtained by the following equation, where p_{min} is the value of the path coefficient with the minimal magnitude in the PLS path model. With a significance level of 5%, $n_{min} > (2.486/p_{min})^2$. Since this method is only suitable for ex post analysis, p_{min} deviates from the value reported in previous studies featuring a similar number of independent variables (Michels, Fecke, et al., 2020; Mohr & Kühl, 2021). Therefore, a p_{min} value of 0.185, which indicates a sample size of 180 respondents at a significance level of 0.05, was estimated in this study.

Statistical requirement verification

The results of the PLS-SEM are evaluated via a two-step process. First, the outer models are analyzed before the structural model (inner model) is evaluated. The decision to measure constructs reflectively or formatively is based on their conceptual nature and causal relationships. Reflective constructs (PU, ITU, and PI) have highly intercorrelated indicators that reflect the underlying variable, with a focus on internal consistency. Formative constructs (PEOU, JR, TR, RI, IT, PS, and PRs) are defined by unique, essential indicators that collectively form the construct. The removal of any indicator from formative constructs would significantly alter its meaning, ensuring that all critical dimensions are considered. The analysis of the reflective model reveals that the quality criteria of the indicators are satisfied. The indicator reliability (loadings ≥ 0.7), convergence validity (average variance extracted (AVE) ≥ 0.5) and internal consistency (rhoA ≥ 0.6) are satisfactory (see Appendix 3) and indicate that the variables of the constructs are appropriate for further analysis (Hair et al., 2021b). In addition, the analysis of the heterotrait-monotrait ratio shows that all values of the reflective factors are below the cutoff value (HTMT < 0.9) and are therefore suitable for the analysis (Hair et al., 2021b) (see Appendix 4). The variance inflation factors (VIFs) of the formative variables are less than five, indicating that no critical levels of multicollinearity are observed. The weights (≥ 0.1) and loadings (> 0.5) are satisfactory and significant (Hair et al., 2021b) (see Appendix 5). Variables of the formative constructs that did not meet these values were excluded from further analysis. Variables may be included in the analysis if they do not meet the above requirements in part, but the t-statistics indicate that they are significant. The variables listed in Appendix 5 contribute to the determination of the formative constructs.

Explanatory power analysis

The structural model represents the hypothesized relationships among different constructs. Since the VIF indicates a value lower than five, no multicollinearity exists with respect to the variables. Some researchers have reported problems with multicollinearity with respect to values ranging between three and five (Becker et al., 2015). This criterion is also satisfied for all but one variable, which slightly exceeds three. The model quality regarding multicollinearity is satisfactory. To determine the explanatory power of the model, the R^2 of the endogenous constructs is examined (Shmueli & Koppius, 2011). To assess statistical significance, the bootstrapping approach with 10,000 subsamples was employed, as recommended by Streukens and Leroi-Werelds (2016). The aim of PLS-SEM is to maximize the R^2 value, and values of 0.75, 0.50 and 0.25 indicate substantial, moderate and low levels, respectively (Hair et al., 2011). The R^2 in our analysis is 0.749, which indicates high explanatory power with regard to the adoption of AI-based camera systems in animal agriculture.

Predictive power analysis

With respect to the analysis of predictive power, however, R^2 serves only conditionally (Hair & Sarstedt, 2021). The $PLS_{predict}$ method (Shmueli et al., 2016) was used to test the predictive power; accordingly, the model was divided into training samples and holdout samples to evaluate the predictive performance of the model (set. seed 123). The root-mean-square error (RMSE) of each indicator of the dependent construct of the structural model was subsequently compared with the RMSE of a naive linear regression model (LM) as a benchmark. One quality criterion is that all indicators should have a lower RMSE in the structural model than in the LM, in which case the model is reliable and has high predictive power (Shmueli et al., 2019). A majority or equal number of lower indicators have moderate predictive power, whereas a minority of lower indicators have weak predictive power (Shmueli et al., 2019). The test in this analysis (Appendix 6) indicates high predictive power with regard to the dependent indicator of the intention to use. Figure 4 shows the full SEM and the influence of the indicators after the prerequisite test.

5. RESULTS

Table 2 shows an overview of the descriptive statistics in comparison with the German average. In our sample, farms have a greater number of animals than the German average in each category. The majority of farmers are aged between 35 and 54 (53.1%) and are thus comparable with German farmers (Federal Ministry of

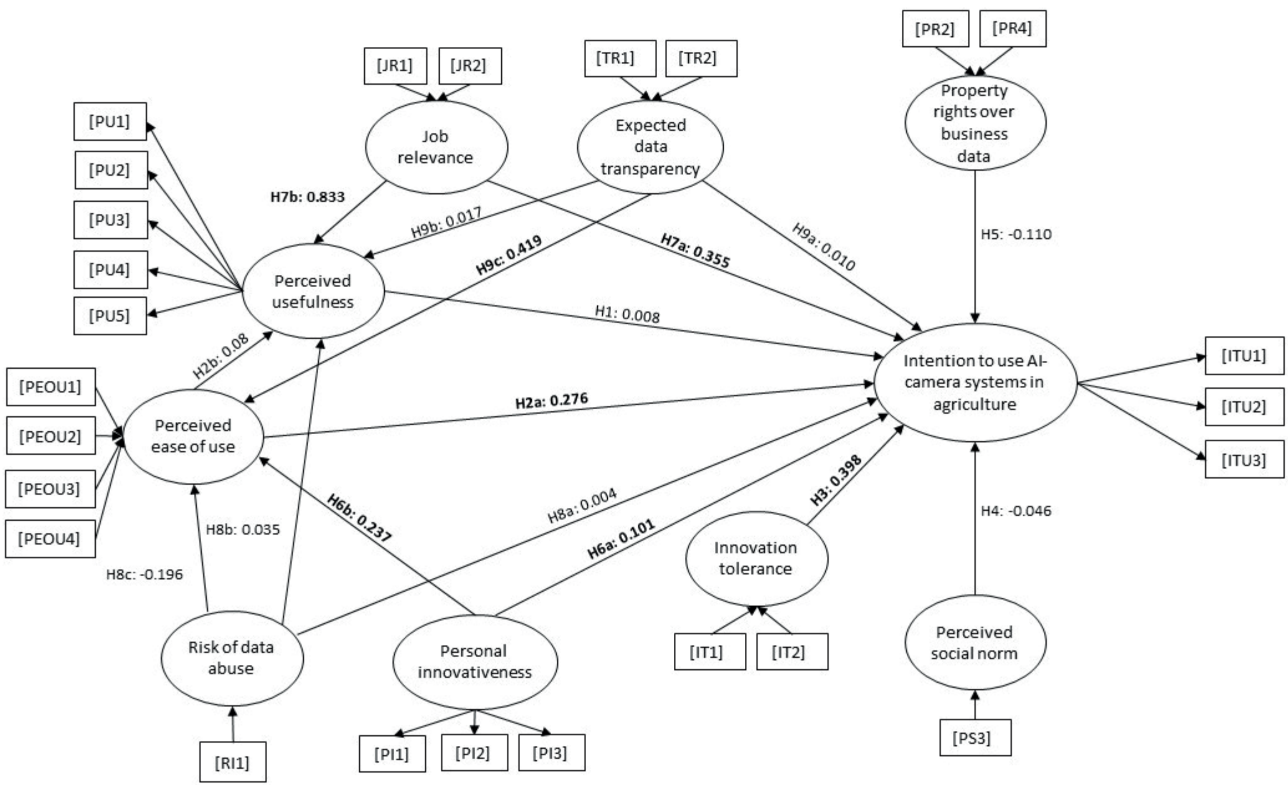

Figure 4. Results of SEM. Legend: Variables that influence the object of investigation are shown in bold.

Table 2. Sample description.

	N=185	German average %
Sex, N (%)		
Female	17 (9.2)	11.25[a]
Male	166 (89.7)	88.75[a]
Other	2 (1.1)	/
Age [years], mean (range)	43.5 (20-72)	53[b]
Vocational education, N (%)		
No formal agricultural degree	6.4	33.2[a]
Vocational or technical school	49.3	57.5[a]
University degree	44.3	9.2[a]
Number of fattening pigs, mean (range)	1282.4 (0-8000)	/
Number of sows, mean (range)	138.0 (0-3000)	/
Number of rearing piglets, mean (range)	663.5 (0-16000)	/
Number of acres [hectares], mean (range)	135.0 (0-5000)	/

[a] Statistisches Bundesamt (2023).
[b] German Farmers Association (2022).

Food and Agriculture, 2023). In terms of gender, the distribution of the sample is different from the average distribution among German farmers, with one-third of the farmers being female. For our sample, we targeted decision-makers on farms, such as owners or directors. The majority (>99%) of our sample identified themselves as decision-makers on their farms. In this context, the distribution of gender is representative with respect to decision-makers on farms (Statistisches Bundesamt, 2023). The participants are more highly educated and younger than the average farmer is.

The analysis shows that seven out of sixteen hypotheses are supported. We obtain empirical evidence for H2a (β =.276, f^2 = .152), H3 (β =.398, f^2 = .213), H6a (β = .101, f^2 = .035), and H7a (β = .355, f^2 = .116), indicating that these constructs are relevant antecedents for the intention to use AI-based camera systems in pig farming. The results for PU and PEOU support H6b (β = .237, f^2 = .083), H7b (β =.833, f^2 = 2.037), and H9c (β = .419, f^2 = .187). Table 3 shows the tested hypotheses, path coefficients, effect size f^2 and t statistics of the model. The path coefficients indicate the direct relationships among the hypothesized constructs in SEM and can be understood as standardized beta coefficients (Hair et al., 2022). In general, the higher the path coefficient is, the greater the relevance of the relationship between the construct and the dependent variable. The analyses revealed that innovation tolerance has the greatest influence on the ITU of all the integrated factors. The F^2 value in SEM measures the effect size of an exogenous construct on the explained variance (R^2) of an endogenous construct.

Table 3. Results of SEM (estimated path co and statistical evaluation measures).

Hypothesis		Path coefficient	Effect size f^2	95%CI		t-Statistics
				LL	UL	
H1	PU → ITU	0.010	0.000	-0.146	0.123	0.138
H2a	PEOU → ITU	**0.276**	0.152	0.150	0.387	2.339
H2b	PEOU → PU	0.08	0.016	-0.008	0.186	1.594
H3	IT → ITU	0.398	0.213	0.241	0.518	5.632
H4	PS→ ITU	-0.046	0.005	-0.160	0.035	-0.909
H5	PR → ITU	-0.110	0.032	-0.168	0.048	-2.078
H6a	PI → ITU	**0.101**	0.035	0.020	0.193	2.339
H6b	PI → PEOU	**0.237**	0.083	0.077	0.404	2.781
H7a	JR → ITU	**0.355**	0.116	0.209	0.517	4.477
H7b	JR → PU	**0.833**	2.037	0.756	0.889	24.563
H8a	RI → ITU	0.004	0.000	-0.074	0.080	0.105
H8b	RI → PU	0.035	0.004	-0.036	0.106	0.977
H8c	RI → PEOU	-0.196	0.038	-0.381	0.003	-2.001
H9a	TR → ITU	0.008	0.000	-0.117	0.067	0.153
H9b	TR → PU	0.017	0.001	-0.063	0.106	0.409
H9c	TR → PEOU	**0.419**	0.187	0.233	0.595	4.432

Legend: ITU: Intention to use; IT: Innovation tolerance; JR: Job relevance; PEOU: Perceived ease of use; PI: Personal innovativeness; PR: Property rights over business data; PS: Perceived social norm; PU: Perceived usefulness; RI: Perceived risk of data abuse; TR: Transparency.

In order to analyze the reliability of the model, a stepwise extension of the original model was performed. The extension showed that both the quality of the model and the influence of the variables changed as a result of the extension. The extension of the classical model showed that the additional factors increased the level of elucidation. The influence on the variance is mainly driven by the factors JR, IT and PI. RI shows no additional explanatory contribution. Other factors such as PS, PR and TR have a rather marginal explanatory power for ITU. Figure 5 shows the evolution of the variance explained (R^2) by the gradual inclusion of the factors.

The path coefficients were also analysed in the context of stepwise extension. JR, IT and PEOU remain the most important influencing factors after the expansion. The change in the other path coefficients is marginal in the course of extension. An exception is PU, which is outweighed by JR after extension and loses importance as a result of further enlargements. Table 4 shows the results in detail.

6. DISCUSSION

The primary objective of this study was to elucidate the factors influencing the intention to use AI-based

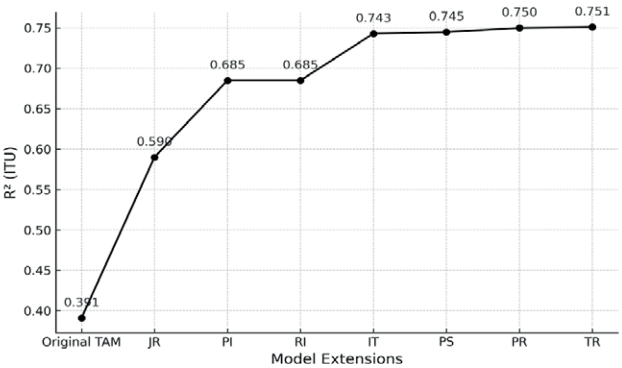

Figure 5. Development of R^2 across model extensions. Legend: ITU: Intention to use; IT: Innovation tolerance; JR: Job relevance; PEOU: Perceived ease of use; PI: Personal innovativeness; PR: Property rights over business data; PS: Perceived social norm; PU: Perceived usefulness; RI: Perceived risk of data abuse; TR: Transparency.

camera systems in German pig farming. Even though our data did not support all the hypotheses, the results showed that user aspects concerning the farmer himself and the perceived ease of use are decisive for the intention to use AI-based camera systems in pig farming. Research on acceptance has been conducted to investigate various technologies within the context of agriculture. Our results are discussed in light of previous findings on technology acceptance in agriculture.

The analyses initially revealed that PEOU [H2a] is one of the most influential factors in the adoption of AI-based camera systems in German pig farming. Previous research confirms these findings. Mohr and Kühl (2021) reported that the PEOU and PI, among other factors, influence the acceptance of artificial intelligence among farmers in general. Other agriculture studies have confirmed this finding with respect to ease of use and acceptance (Michels et al., 2021). The transferability of the results to different agricultural sectors is reinforced by a study related to precision livestock farming, which revealed that visualization and PEOU influence the acceptance of a system (van Hertem et al., 2017).

In our study, innovation tolerance [H3] had the greatest impact on the intention to use AI-based camera systems in pig farming. The interpretation of the results of IT can be assigned to the person himself or herself, which incorporates a self-image consisting of risk affinity and the estimation of the future importance of this technology. This finding is in consistent with the literature, which states that risk aversion (Abadi Ghadim & Pannell, 1997) or the willingness to take risks (Seibert et al., 2021) determines the intention to use a new technology. This construct also supports the assumption that a positive view of the importance of the technology in the future is decisive for the intention to use it (Rogers, 2003). Although the empirical results show a dominant contribution of IT2, while IT1 exhibits a low weight and loading. This suggests that the construct is essentially driven by the specific item on AI-related attitudes, and the general trait-based indicator contributes minimally. Future research should consider refining the indicators to ensure a more balanced and representative operationalization of the construct.

In this study, the influence of personal innovativeness [H6a] on the intention to use AI-based camera systems was demonstrated. This construct has a statistically significant positive influence on the acceptance of AI-based camera systems in our sample, indicating that the intention to use increases with increasing innovativeness. Although the influence of this construct on the dependent latent variable is low, it can still explain acceptance to some extent. Previous studies from Agarwal and Prasad

Table 4. Development of path coefficients.

	Number models								
	PU→ ITU	PEOU → ITU	JR→ ITU	PI → ITU	RI → ITU	IT→ITU	PS → ITU	PR → ITU	TR → ITU
Original TAM model	0.507	0.383	-	-	-	-	-	-	-
2 (+ JR)	0.073	0.308	0.557	-	-	-	-	-	-
3 (+ PI)	0.057	0.289	0.543	0.111	-	-	-	-	-
4 (+ RI)	0.057	0.290	0.545	0.111	0.005	-	-	-	-
5 (+ IT)	-0.006	0.236	0.361	0.098	0.029	0.374	-	-	-
6 (+ PS)	-0.005	0.242	0.365	0.095	0.027	0.400	-0.057	-	-
7 (+ PR)	0.009	0.252	0.358	0.097	0.027	0.418	-0.041	-0.083	-
8 (+ TR)	0.010	0.276	0.355	0.101	0.004	0.398	-0.046	-0.110	0.008

Legend: ITU: Intention to use; IT: Innovation tolerance; JR: Job relevance; PEOU: Perceived ease of use; PI: Personal innovativeness; PR: Property rights over business data; PS: Perceived social norm; PU: Perceived usefulness; RI: Perceived risk of data abuse; TR: Transparency.

(1998) and Aubert et al. (2012) have identified PI as an influencing variable. This construct serves to identify early adopters as agents of innovation and should be considered an important factor in implementation processes in agriculture. This finding contradicts the results reported by Mohr and Kühl (2021), who found only an indirect influence of PI on acceptance. This indirect influence [H6b] was also supported by our data. Notably, in the case of the cited study, AI was considered in general, and the measurement of PI was made more difficult by a generalization of the subject of the study.

The statistical analysis of the survey results revealed another construct that has a statistically significant influence on the ITU: the perceived relevance of the technology for the farming profession [H7a]. The influence of JR on acceptance and adoption in the context of agricultural technologies was also demonstrated by Michels et al. (2021). The authors analyzed the acceptance of drone technology and demonstrated that JR has the greatest influence on the ITU. In conclusion, for practice and the development of new AI-based monitoring systems, it is important to communicate precisely the benefits for everyday working life.

Although the statistical measurements were not statistically satisfactory overall, this study demonstrated that expectations of data ownership have an effect on the intention to use [H5]. In contrast to other studies, our approach assumed a negative effect of stronger expectations regarding data rights. According to the variables PR2 and PR4 within the final construct and PR1 outside of the construct, the importance of data ownership to farmers determines their intention to use AI-based camera systems. An undefined ownership structure of the data is assumed to lead to rejection of the technology. Previous studies have also shown that in the context of German citizens and electronic data, German Angst plays a central role in the adoption, acceptance, and design of institutions (Akkaya et al., 2012).

Other constructs (e.g., PU, TR and RI) did not influence the intention to use AI-based camera systems in this sample. This finding contradict the conclusions of Krempel and Beyerer (2014), whose research on surveillance cameras showed that the transparency of the data processed was one of the most important factors regarding acceptance. This difference may be due to the type of AI surveillance. Furthermore, low perceived transparency as a barrier may have an important influence on farmers' intention to use risk management tools (Giampietri et al., 2020). While PU [H1] is a crucial factor according to many studies on the acceptance of technology in agriculture (Michels, Fecke, et al., 2020; Michels et al., 2021), it is not relevant in our statistical model or in studies on the acceptance of AI in general (Mohr & Kühl, 2021). On the one hand, this difference may be because the PU can be accepted or rejected independently of the ITU. Thus, a rejection of the intention to use is not synonymous with the system's lack of actual usefulness. On the other hand, the rejection of AI-based camera systems despite a perceived high or very high benefit is due to other factors, such as a lack of PEOU. This finding was not only supported by the full SEM, but also by the stepwise inclusion of the factors and the resulting development of the path coefficients. It can be concluded that PU has an influence on the original model, but that is outweighed by, among other things, the introduction of JR. On the one hand, this effect could derive by the fact that both variables measure similar characteristics in the occupational context. On the other hand, there are indications in our model that there is a stronger relationship between JR and ITU in the adaptation of technologies by the decision makers, as apparently the relevant professional context is more important than the actual usefulness.

An additional consideration in the context of modelling and hypothesis generation is the differentiated role of individual factors, whether as direct determinants, potential mediators, or moderators within the model structure. In the present model, it may be hypothesized that PI exerts a moderating influence on ITU, as it reflects, at least in part, trait-like characteristics of the respondents. While the conceptual phase of theory-driven hypothesis development did not provide sufficient justification for including such a moderation effect, theoretical reflections combined with the empirical findings of this study suggest that future analyses should explicitly consider this possibility.

Besides the findings of our model applying an extended TAM, other approaches should be used to investigate the ITU of AI camera systems. For example, the TPB could be an appropriate model for further research. In the case of animal husbandry and the monitoring of health and welfare parameters, TPB constructs would help to identify voluntary action by farmers in technology adaptation. An investigation of TPB factors would help to provide important insights for the development of systems and recommendations for policy, particularly in the highly regulated area of agriculture and AI. Especially in a policy context where voluntarism is the preferred option for adaptation over regulation.

Apart from the analysis of behavioral factors further research on the technology itself is also needed. It is equally important to know which economic and technology-specific factors, in addition to behavioral factors, moderate the potential adaptation. For new technologies with a specific field of application, Sok and Hoestra (2023) used the subject of electrified tractors to show that uncertainty about the economic benefits and cost-effectiveness were the most important factors for the decision of the farmers surveyed. An examination of the economic and technology-specific factors using random utility theory would provide further clarification on the possible adoption or rejection of AI camera systems and help companies and policymakers to create the necessary framework conditions for market integration. Since analyses of non-behavioral factors (e.g. age, education, farm size) have shown little influence on the adaptation of AI camera systems in pig farming (Kühnemund & Recke, 2024), consideration of the TPB and economic factors could help to explain the variance in the intention to use.

Our study is limited by the notion that the results must be understood considering the specific types of animal farmers. Therefore, these results are only partially applicable to other forms of livestock production. Especially in the case of highly integrated value chains that focus on the interests of the integrator, other factors could lead to acceptance or rejection, which were not considered in this study. The results must also be viewed in consideration of the convenience sample and do not constitute a representative analysis of the object of investigation. Therefor the findings are not generalizable to the overall population of German pig farmers. For further studies a representative sampling strategy should be applied in order to investigate models like TPB or random utility theory. Although Germany is one of the largest pig-producing countries in Europe and even worldwide, the results cannot be applied uniformly at the international level. Cultural idiosyncrasies, the strongly male-dominated agricultural sector and the formal institutions involved in handling the data in this context are only some of the reasons why the results cannot be fully generalized to a European or global context. It is possible that the survey procedure (online survey) causes selection bias because the survey invitation only reached people who were on the mailing list and may also have addressed those who are interested in technology. Despite these limitations, this study provides important findings for future research on and the development of AI-based camera systems. This study is characterized by a sample that corresponds to the characteristics of German pig farmers. Furthermore, the necessary sample size was achieved, increasing the robustness of the analysis. The model showed satisfactory performance, which emphasizes the significance of the results.

Knowledge of development and the factors that promote successful implementation are essential for practitioners as well as for policy and regulatory decision-makers. A technology is useful only if it is used by the target group. Future research should focus on user-friendly interfaces. In terms of simplicity, it is also important to ensure low-barrier access to the technology and to create an infrastructure that makes these systems easy to use for all farmers. In addition, it is conceivable that the target group and potential users could be reached through farmers who have already had experience with the system. In addition, the legal component should be explored by investigating the influence of such institutions. The results show that developers should focus on the benefits and application to the farmer's job. The economic relevance of AI-based camera systems, as well as their potential to generate added value at specific stages of the livestock production process, should be more explicitly identified and communicated. Their implementation could offer targeted solutions to current challenges, such as the early detection and prevention of tail biting in undocked pigs or the reduction of labor-intensive, legally mandated animal observation tasks that currently lack direct economic return. In addition, attention should be paid to ease of use to ensure successful market integration. The analysis also suggests that AI camera systems should be further developed in collaboration with tech-savvy farmers to address their enthusiasm for innovation. Incorporating this technology into an intelligent housing system could lead to successful integration with other solutions such as housing climate and feeding. Policy makers should create the basis for such compatibility in order to increase the uptake of technologies. In addition to clear frameworks for transparency and legal certainty of data, policymakers and educational institutions should integrate educational programs into the training of farmers to facilitate the use of new AI technologies. This can lead to future farmers being more open to innovation.

7. CONCLUSION

In summary, the perceived ease of use, innovation tolerance, job relevance, and personal innovativeness emerged as influential constructs that shape the intention to use AI-based camera systems in pig farming. Understanding the behavior-based acceptance of AI technologies is crucial, and the factors identified in this study can guide the development of AI-based camera systems that are embraced by farmers and offer tangible benefits. In this sample, the general acceptance of an AI-based camera system was high; to support real adoption, the identified influencing factors should be considered. Evidence synthesis showed that influential constructs depend on the sample composition and the research object

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APPENDIX 1: HYPOTHESES

H1: The perceived usefulness of AI-based camera systems in pig livestock farming has a positive effect on the intention to use AI-based camera systems in pig livestock farming.

H2a: The perceived ease of use of AI-based camera systems in pig livestock farming has a positive effect on the intention to use AI-based camera systems in pig livestock farming.

H2b: The perceived ease of use of AI-based camera systems in pig livestock farming has a positive effect on the perceived usefulness of AI-based camera systems in pig livestock farming.

H3: Innovation tolerance has a positive effect on the intention to use AI-based camera systems in pig livestock farming.

H4: Perceived social norms have a positive effect on the intention to use AI-based camera systems in pig livestock farming.

H5: The expectation of property rights over business data has a negative effect on the intention to use AI-based camera systems in pig livestock farming.

H6a: The personal innovativeness of farmers has a positive effect on their intentions to use AI-based camera systems in pig livestock farming.

H6b: The personal innovativeness of farmers has a positive effect on the perceived ease of use of AI-based camera systems in pig livestock farming.

H7a: Job relevance has a positive effect on the intention to use AI-based camera systems in pig livestock farming.

H7b: Job relevance has a positive effect on the perceived usefulness of AI-based camera systems in pig livestock farming.

H8a: The perceived risk of data abuse has a negative effect on the intention to use AI-based camera systems in pig livestock farming.

H8b: The perceived risk of data abuse has a negative effect on the perceived usefulness of AI-based camera systems in pig livestock farming.

H8c: The perceived risk of data abuse has a negative effect on the perceived ease of use of AI-based camera systems in pig livestock farming.

H9a: Expected data transparency has a positive effect on the intention to use AI-based camera systems in pig livestock farming.

H9b: Expected data transparency has a positive effect on the perceived usefulness of AI-based camera systems in pig livestock farming.

H9c: Expected data transparency has a positive effect on the perceived ease of use of AI-based camera systems in pig livestock farming.

APPENDIX 2: ITEMS AND DESCRIPTIVE STATISTICS

Factor name	Factor description	Mean	SD
To what extent do you agree with the following statements? I think that…			
ITU1	… I will additionally observe my animals using cameras.	3.65	1.22
ITU2	… I will use cameras in my business in the future.	3.49	1.25
ITU3	… I would use cameras on my farm.	3.65	1.22
To what extent do you agree with the following statements? I think that the use of AI-based camera systems…			
PU1	… allows me to do work in the barn more quickly than before.	2.98	1.23
PU2	… facilitates the work of all employees on my farm.	3.05	1.24
PU3	… increases the productivity of my business.	3.20	1.16
PU4	… reduces my overall workload on the farm.	3.05	1.19
PU5	… gives me more flexibility in terms of my operating processes.	3.23	1.15
To what extent do you agree with the following statements? For me, …			
PEOU1	…operating AI cameras to observe animals is easy to learn.	3.79	0.95
PEOU2	… videos from animal observation cameras are easy to evaluate.	3.25	1.07
PEOU3	… working with cameras to observe animals in the barn is possible without technical problems.	3.13	1.09
PEOU4 (R)	… it is difficult to operate AI cameras and evaluate videos.	3.67	1.11
To what extent do you agree with the following statements? I think that…			
JR1	… the use of AI cameras can be relevant to my work.	3.54	1.15
JR2	… the use of AI cameras can have a high degree of relevance for my operations.	3.06	1.17
JR3	… AI cameras are suitable for my business.	3.16	1.15
To what extent do you agree with the following statements? I think that…			
TR1	… I am well informed about what data are captured by a camera-based image processing system.	2.92	1.15
TR2	… I am well informed about how such a system processes data.	2.76	1.17
To what extent do you agree with the following statements? I think that…			
RI1	… I could be disadvantaged by errors in the collection or processing of data by the system.	3.10	1.10
RI2	… (image) data could be misused.	3.62	1.23
To what extent do you agree with the following statements?			
IT1	I consider myself to be a risk taker.	3.24	0.93
IT2	I think it will be important in the future to use AI cameras for animal observation.	3.25	1.19
To what extent do you agree with the following statements?			
PI1	I enjoy being around people who are trying out new technologies.	4.03	0.84
PI2	I am very curious about how new agricultural technologies work.	4.07	0.91
PI3	I like to try out new agricultural technologies.	3.84	0.92
PI4	I often determine information about new technologies.	4.10	0.82
To what extent do you agree with the following statements?			
PS1	The German population has a positive view of modern technology in agriculture.	2.61	0.99
PS2	Policy-makers support modern agriculture.	1.84	0.90
PS3	I think that the use of AI camera monitoring in barns is consistent with society's expectations of agriculture.	3.09	1.13
To what extent do you agree with the following statements?			
PR1	Corporate data belongs to the farmers.	4.78	0.55
PR2	Stronger regulation for data security reduces the competitiveness of German farmers.	2.40	1.10
PR3	The government should create a data platform for sharing agricultural data.	2.09	1.07
PR4	As long as I receive large benefits from it, I do not care if companies use operational data.	2.11	1.21
PR5	The data flow of visual material should be controlled by farmers.	4.40	1.12

Legend: ITU: Intention to use; IT: Innovation tolerance; JR: Job relevance; PEOU: Perceived ease of use; PI: Personal innovativeness; PR: Property rights over business data; PS: Perceived social norm; PU: Perceived usefulness; RI: Perceived risk of data abuse; TR: Transparency.

APPENDIX 3: REFLECTIVE CONSTRUCTS

Reflective measurement models	Indicator name	Indicator reliability Loadings	Convergent validity AVE	Internal consistency rhoA	rhoC	Cronbach's Alpha
Intention to use AI-based camera systems	ITU1	0.942	0.898	0.944	0.964	0.943
	ITU2	0.955				
	ITU3	0.946				
Perceived usefulness	PU1	0.847	0.722	0.907	0.928	0.903
	PU2	0.825				
	PU3	0.876				
	PU4	0.865				
	PU5	0.835				
Personal innovativeness	PI1	0.871	0.729	0.827	0.90	0.815
	PI2	0.856				
	PI3	0.834				

Legend: ITU: Intention to use; PI: Personal innovativeness; PU: Perceived usefulness.

APPENDIX 4: HETEROTRAIT–MONOTRAIT

	Perceived usefulness	*Personal innovativeness*	*Intention to use*
Perceived usefulness	.	.	.
Personal innovativeness	0.366	.	.
Intention to use	0.742	0.443	.

APPENDIX 5: FORMATIVE CONSTRUCTS

Formative measurement models	Indicator name	VIF	Weight	Loadings
Perceived ease of use	PEOU1	1.723	0.380	0.776
	PEOU2	1.753	0.482	0.849
	PEOU3	1.467	0.446	0.809
	PEOU4	1.342	-0.199	0.329
Job relevance	JR1	2.943	0.407	0.920
	JR2	2.317	0.185	0.817
	JR3	2.327	0.509	0.931
Perceived risk of data abuse	RI1	1.169	0.941	0.992
Innovation tolerance	IT1	1.045	0.079	0.283
	IT2	1.045	0.981	0.997
Perceived social norm	PS3	1.057	0.979	0.997
Property rights	PR2	1.360	0.559	0.797
	PR4	1.151	0.379	0.629
Transparency	TR1	1.196	0.481	0.766
	TR2	1.196	0.703	0.898

Legend: IT: Innovation tolerance; JR: Job relevance; PEOU: Perceived ease of use; PR: Property rights over business data; PS: Perceived social norm; RI: Perceived risk of data abuse; TR: Transparency.

APPENDIX 6: PREDICTIVE POWER

	ITU1	*ITU2*	*ITU3*
RMSE (PLS)	0.733	0.741	0.768
RMSE (LM)	0.761	0.773	0.829

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Digital technology adoption among italian farmers: An extended technology acceptance model approach in the horticultural sector

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Abstract. The adoption of digital technologies in agriculture is essential for enhancing sustainability, productivity, and resource efficiency. This study investigates the factors influencing Italian horticultural farmers' adoption of innovative water-smart agricultural technologies using an extended Technology Acceptance Model (TAM3). The research employs a structured survey conducted with 251 Italian farmers, analysing their perceptions of technology usefulness, ease of use, social norms, and sustainability outcomes. Structural equation modelling (SEM) confirms that perceived usefulness significantly influences adoption intentions, while perceived ease of use plays a limited role. Social norms and sustainability-related benefits also emerge as critical determinants. Results also indicate the impact of farm size and workforce on adoption behaviour. These findings highlight the need for targeted policies, training programs, and financial incentives to overcome adoption barriers. The study provides insights for policymakers, technology developers, and agricultural stakeholders to foster digital innovation in the horticultural sector, contributing to sustainable water management practices.

Keywords: digital agriculture, farmer adoption, Technology Acceptance Model (TAM), horticultural sector, water-smart sustainable farming.

HIGHLIGHTS

- A structured survey conducted with 251 Italian horticultural farmers
- The extended TAM3 explains 18% of the variance in the behaviour (the adoption of water-smart technologies), and 65% of the variance in intention
- Behavioural intention is a significant predictor of the behaviour
- Perceived usefulness and social norms have a significant effect on adoption intention
- Perceived ease of use has no influence on adoption intentions

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1. INTRODUCTION

The agricultural sector is facing many unprecedented challenges. These include the need to develop sustainable resource management strategies to meet the growing demand for food and to reduce the environmental impact of agri-food production (Kapsdorferová, 2024). Given the increasing pressure on agricultural systems, in particular on natural resources, it is crucial to identify effective measures to mitigate these negative impacts in line with the European Green Deal and the United Nations 2030 Agenda (Montanarella and Panagos, 2021). In this context, the application of digital technologies and the development of smart solutions have emerged as key strategies to improve efficiency, productivity and sustainability in the agri-food sector (Yigezu et al., 2018). Among the various forms of agricultural innovation, practices related to irrigation are of particular importance today (Asadi et al., 2020). Water scarcity and drought are now considered a global problem of paramount importance, that is likely to be exacerbated by climate change, which is one of the greatest environmental, social and economic challenges facing the entire planet (Ermolieva et al., 2022; Ungureanu et al., 2020). Water-smart agricultural practices can be helpful in two ways: from an environmental perspective, they can reduce pressure on water resources, improve water use efficiency and reduce water waste. From an economic perspective, these solutions can lead to cost savings and productivity increases and contribute to overall profitability by maximizing crop yields per amount of water used (Gemtou et al., 2024). The use of specific innovations, such as soil moisture sensors, automatic irrigation systems and predictive models has the potential to address major challenges such as water scarcity and the impact of climate variability (Adeyemi et al., 2017), as well as energy savings (Patle et al., 2019). However, one of the biggest challenges facing smallholder agriculture is the low uptake of innovative technological solutions, which has led to relatively low technology penetration in the sector (Senyolo et al., 2018). In this context, it is crucial to gain insights into farmers' behaviour, their willingness to adopt smart solutions and potential strategies to facilitate wider adoption of water technologies in the agricultural sector (Gemtou et al., 2024).

It is evident that despite the general focus on a fair transition from agricultural practices to digital technologies, the diffusion and adoption of smart technologies remains uneven and is influenced by a complex interplay of individual, technological and contextual factors (Shang et al., 2021). Previous studies have shown that there are significant differences in adoption rates among farmers (Paustian and Theuvsen, 2017).

Farmers' decision-making processes, which are shaped by perceptions of benefits, ease of use and external pressures, are key to understanding the adoption landscape (Cimino et al., 2024; Schulze Schwering et al., 2022). Given the limited technological penetration of the agricultural sector and the potential benefits of digital technologies, it is crucial to investigate the factors influencing the adoption of smart technologies (Gemtou et al., 2024).

While previous research has investigated adoption patterns among farmers, it has often focused on large-scale farming operations or specific regions with advanced technological infrastructures (Paustian and Theuvsen, 2017). Additionally, studies have highlighted barriers such as limited digital literacy, financial constraints, and a lack of institutional support for small and medium-sized farms (Senyolo et al., 2018; Shang et al., 2021). Despite this growing body of work, several gaps in the literature remain. First, little research has focused on the adoption of water-smart technologies in the horticultural sector, which plays a crucial role in agricultural sustainability. Most studies on precision agriculture have examined large-scale cereal farming, neglecting horticultural systems where irrigation efficiency is a key factor (Adeyemi et al., 2017). Second, while research has investigated the impact of farm size and socio-demographic characteristics on technology adoption, the role of sustainability considerations and social norms remains underexplored. Previous studies have suggested that perceived usefulness and perceived ease of use drive adoption, but the extent to which sustainability motivations influence farmers' decisions is not well understood (Gemtou et al., 2024). Finally, existing literature has rarely examined the adoption of digital technologies in Italian agriculture, a sector characterized by fragmented land ownership, diverse regional farming practices and different levels of technological readiness (Baldoni et al., 2018).

This study aims to address these gaps by analysing the factors influencing Italian farmers in the adoption of digital technologies for better water management and the barriers they face, with a focus on horticultural crops. Horticulture has been considered for some reasons: first, because of the importance of this sector in the Italian agricultural system; secondly, for the relevance of the irrigation in this cropping system (Patle et al., 2019); third because of the relevance of smart precision in horticulture (Adeyemi et al., 2017). The technologies studied relate to smart water management through a three-stage technology complexity: the first (basic) stage is represented by the introduction of soil moisture sensors, which proceeds to a system that combines sensors with an automatic irrigation system, and in the last stage the sensors are connected to an automated system, which in turn is connected to and dialogs with predictive models[1]. Understanding how these farmers perceive and adopt water-efficient innovations is crucial to develop targeted policies, design effective incentives, and promote sustainable agricultural practices. The results of this work can provide valuable insights to policymakers, technology providers, and other stakeholders (e.g., cooperatives, producers' associations, etc.) seeking to promote sustainable and efficient agricultural practises through innovation.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

As the existing literature shows, the process of adopting new technologies is inherently complex and dynamic (Montes de Oca Munguia et al., 2021). In particular, the decision-making process is influenced by various factors that affect the rate of technology adoption by farmers (Gemtou et al., 2024; Osrof et al., 2023). Although the existing literature has explored the mechanisms of innovation diffusion, there does not seem to be a unified set of theories or models that could explain the phenomenon. Some authors have highlighted the specificity of theories in modelling different aspects of the technology adoption process (Dissanayake et al., 2022; Osrof et al., 2023), while others have expressed doubts about the generalist ability of theories to represent different technologies and practices (Montes de Oca Munguia et al., 2021). Indeed, there is still confusion about the methods of analysis and the choice of explanatory variables that should be used to model the adoption process (de Oca Munguia and Llewellyn, 2020). To illustrate, Shang et al. (2021) argue that the mechanisms of adoption and diffusion of digital agricultural technologies need to be understood at both the farm level and the system level. They also suggest that the focus in determining technology diffusion should be on system interactions in combination with individual characteristics. Given the evidence presented in the literature, it can be assumed that the categories of individual, technological, social and economic factors influencing technology adoption can describe the entire decision-making process (Dissanayake et al., 2022). There is a clear lack of convergence and consistency in the results regarding the impact and statistical significance of the individual factors assessed in the adoption models (de Oca Munguia and Llewellyn, 2020). This discrepancy can be attributed to the fact that most adoption studies do not include variables on technologies or practices. It is recognized that the use of multiple paradigms in modelling technology adoption and diffusion can increase the explanatory power of the models. However, it is important to consider the factors and their interactions in a way that is consistent with the objectives and context of the study within a specific food system (Dentoni et al., 2023).

In the present work we applied the Technology Acceptance Model (TAM) (Davis, 1989) for measuring the intention of Italian farmers to adopt innovative smart technologies. According to this paradigm, two dispositions towards a new technology (perceived usefulness and ease of use) determine a person's attitude towards using that technology and influence their desire to use it. Perceived usefulness is the extent to which a person believes that job performance can be enhanced by using the new technology, whereas perceived ease of use is the extent to which a person believes that using the new technology is effortless. Some extensions of the original TAM conceptualization have been proposed, such as the TAM3 version (Venkatesh and Bala, 2008). The TAM3 extension introduces new constructs and determinants that affect the core variable perceived ease of use and proposes new relationships between the constructs. The factors influencing perceived ease of use in the TAM3 version are computer self-efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability, whereas perceived usefulness is affected by subjective norm, image, relevance to work, output quality and demonstrability of results. Other innovations introduced by this extension include: (i) the correlation between perceived ease of use and perceived usefulness, (ii) the correlation between perceived ease of use and intention, and (iii) the concept of anxiety. The latter factor, which expresses the degree of emotional fear, apprehension, nervousness, or stress experienced when interacting with a new technology, is supposed to negatively affect the perceived ease of use. The more anxiety a person feels, the less likely they are to perceive the technology as easy to use.

Some minor adjustments were made to the original TAM3 version by Venkatesh and Bala (2008) to better suit the purpose and context of the analysis. First, all constructs were considered in the context-specific environment, i.e. the adoption of new water-smart agricultural technologies by Italian horticultural farms.

[1] Specifically, automatic irrigation systems are connected to sensors that monitor soil moisture and activate valves wirelessly; instead, predictive modelling integrates the first two solutions (soil moisture sensors and automatic irrigation systems) into predictive models that merge real-time data with historical data, analyse it, and make autonomous irrigation decisions thanks to water delivery schedules that optimize dosing based on specific crop requirements and environmental conditions.

Moreover, some aspects were evaluated as very important and emerged explicitly from the exploratory phase with the participants, such as technology self-efficacy and quality of outcomes. Other characteristics, such as (computer) playfulness or perceived enjoyment, that are characteristic of the original conceptualization of the TAM3 model in relation to information technologies, do not apply to the context of the current research and were therefore excluded from the model design. Then, some variables were found to be significant when considering sustainability issues (Gemtou et al., 2024). Consequently, a category based on with the Sustainability Assessment of Food and Agriculture Systems (SAFA) (FAO, 2014) was included in the model. More specifically, the themes inspired by the FAO-indicators were (i) the reduced water-used thanks to the optimization of the irrigation system, (ii) the improved skills the employees and the holder/farmer need to reach to use the technology, and (iii) new employees recruited thanks to their technological skills. Therefore, we tested the following main hypotheses on the factors influencing the adoption of new water-smart agricultural technologies by Italian horticultural farms (Figure 1):

H1: perceived usefulness is positively affected by output quality (H1a), by sustainability outcomes measured by SAFA indicators (H1b), and by subjective norms (H1c);
H2: perceived ease of use is positively affected by technology self-efficacy (H2a), and is negatively affected by anxiety (H2b);
H3: perceived ease of use has a positive impact on farmers' intention to adopt new technologies (H3a), and is positively affecting the perceived usefulness of new technologies (H3b);
H4: perceived usefulness has a positive impact on farmers' intention to adopt new technologies;
H5: subjective norms have a positive impact on farmers' intention to adopt new technologies;
H6: the farmers' intention to adopt new technologies is positively affecting the behaviour, i.e. the new technology adoption.

Moreover, individual factors, such as socio-demographic and organizational factors, which determine the natural and structural conditions of the farm, have been found to correlate with farmers' decisions. In particular, farmers' education level, gender, age, technology literacy, were among the individual drivers more frequently included in studies investigating the smart farming technologies adoption (Osrof et al., 2023). Farm size, mostly

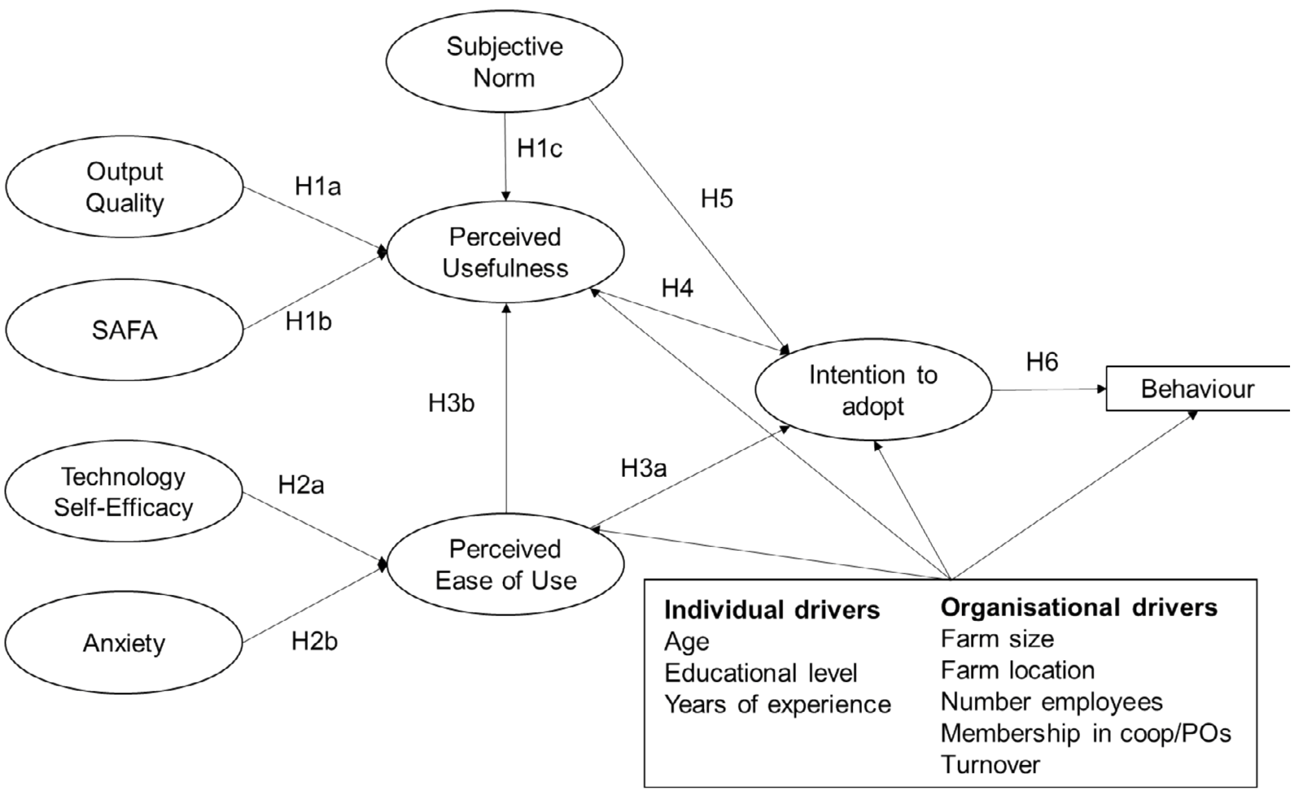

Figure 1. Model testing the factors affecting the adoption of water-smart agricultural new technologies by Italian horticulture farms.

expressed in total acreage farmland, is a prominent factor among the organizational ones, since larger farm size is consistently seen as pivotal for achieving economies of scale when adopting smart farming technologies. Farm income is another key element, as farmers with a higher income are more willing to invest in new technologies (Osrof et al., 2023). Farm location is also a notable barrier within this theme, showing mixed effects in past studies. Some research indicates that it might negatively affects farmers' motivation to adopt smart technology, particularly if farms face unfavourable climate conditions or soil quality (Paxton et al., 2011). In Italy, farms in the northern regions are generally more competitive, due to larger farm sizes, advanced mechanisation, and stronger market integration. In contrast, farms located in central and southern regions often face structural constraints, including smaller farms and lower productivity (Baldoni et al., 2018). Other studies emphasize the importance of social factors and access to information for the adopting of innovative smart technologies (Blasch et al., 2022). In this context, being a member of a farmers' associations or a producer organizations (POs), where knowledge transfer is one of the main objectives, might facilitate adoption. Therefore, we controlled the main endogenous variables of the model, i.e. perceived usefulness, perceived ease of use, adoption intention and behaviour, with individual factors, namely farmers' age, education level and years of experience in the agricultural sector, and organizational ones, including farm size, farm location (expressed by the latitude of the province where the farm is located), number of employees, membership in a cooperative or a producer organization, and farm turnover (Figure 1).

3. DATA AND METHOD

3.1. Data collection

The data collection consisted in two phases: first we conducted a preliminary exploratory phase with qualitative, unstructured interviews. The aim of the exploratory interviews was to identify relevant aspects to be included in the final model and to highlight those that could be omitted. In this way, relevant points such as the quality of results and self-efficacy were included in the final surveys. The questions focused on previous experience with smart technologies, skills in using them, public financial support for the adoption of technical solutions and the farm structure, as well as farmers' previous personal background. In the second phase, we conducted a survey among a sample of Italian horticultural farms. After an initial pilot phase (n=21 interviews) to test the questionnaire, the main study was conducted in the period from October to November 2024 by an international market research company using the CATI (Computer Assisted Telephone Interview) method. The survey lasted approximately 30 minutes. The total defined sample consisted of 251 Italian farmers.

The sample includes farmers who grow tomatoes (50% in northern Italy and 50% in the south), and those who grow fresh vegetables, such as carrots, peppers, eggplants, lettuce, etc., spread across northern, central and southern Italy (30%, 17%, and 53%, respectively).

The geographical breakdown was chosen to be representative of the horticultural farms according to the Italian National Institute of Statistics (ISTAT). The coverage of different administrative regions throughout Italy ensures a comprehensive understanding of cultivation practices across the country and also illustrates the different technological levels.

3.2. Measures

Together with the socio-demographic information and the descriptive indicators, the questionnaire was designed to test the model hypotheses. Overall, it included 14 constructs, with a total of 45 items. The constructs included in the final model (Figure 1) were aimed to understand the drivers for the adoption of innovative water-smart agricultural technologies by Italian horticultural farms. All TAM3 items were measured on a 7-point scale (from 'strongly disagree' to 'strongly agree') (see Annex Table A1).

Subjective norm, i.e. the perceived social pressure to adopt the new technology, was assessed by three items (e.g., "Many producers I know have already adopted this innovation"). We measured the perceived usefulness with four items (e.g., "This innovation could improve my productivity"). Output quality, i.e. the perception of the quality of the technology in performing the task, was measured by four items (e.g., "Using this technology will improve the quality of my products"), whereas SAFA-based aspects (i.e. the sustainability-related outcomes of the new technology adoption) were assessed by four items (e.g., "By using this innovation, I could help reduce water consumption"). We used two items for assessing the perceived ease of use (e.g., "This technology should be easy to use"). Technology self-efficacy, i.e. the belief in how well someone can perform actions to achieve performance outcomes, was measured by three items (e.g., "I would use this innovation easily if I had technical support"), whereas anxiety was assessed by three items (e.g., "New technologies make me feel uncomfortable"). We used three items to assess behavioural intention (e.g., "I intend to use this technology in the near future").

The study focused on the three levels of water-smart technologies described above: Level 1) – soil moisture sensors, Level 2) – a system combining sensors with an automatic irrigation system, and Level 3) – sensors connected to an automated system, which in turn is connected to and interacts with predictive models. If a farmer indicated they have adopted a certain level of the technology, the items were framed for the next level. For instance, if a respondent have already adopted soil moisture sensors, we asked about the intention to adopt the sensors connected to an automated system. If no adoption was reported, we asked about their intention to adopt soil moisture sensors (Level 1), whereas when they reported the highest level of adoption, we asked about the intention to adopt more advanced predictive models. Therefore, the behaviour was assessed with a single item, ranging from 1 to 4, considering the different adoption levels (1=no technology; 2=Level 1; 3=Level 2; 4=Level 3).

3.3. Data analysis

We performed the statistical analysis using SPSS v.29.0 and AMOS v.29.0 statistical software (IBM Corporation, Armonk, NY, USA). Means, standard deviations, median and interquartile range (IQR) were calculated for each questionnaire item and its related construct. Structural equation modelling (SEM) was used to test hypotheses H1–H6 and the theoretical framework in Figure 1. SEM allows models to be specified with both latent (e.g., perceived usefulness) and observed variables (e.g., farmer's age) (Kline, 2016). Specifically, we have considered two models: in Model 1 we included only the variables of the extended-TAM3 model (i.e. behaviour, behavioural intention, subjective norm, perceived usefulness, perceived ease of use, output quality, SAFA, technology self-efficacy and anxiety). Then, we controlled for the effects of individual factors (i.e., farmers' age, educational level, and years of experience in the agricultural sector) and organizational factors (i.e., farm size, farm location, number of employees, membership in a cooperative or a producer organization, and farm turnover) on the endogenous variables (i.e., perceived usefulness, perceived ease of use, behavioural intention, and behaviour) by adding them step by step to Model 1. We then run Model 2 by adding to Model 1 the significant effects of the individual and organizational factors previously found. Convergent validity of the model variables was assessed using average variance extracted (AVE), Cronbach's α coefficient, and composite reliability (CR). Discriminant validity was tested by comparing the square root of the AVE of each construct with the inter-construct correlation (Bagozzi and Yi, 2012). The goodness-of-fit of the models was assessed using the χ^2 and their degrees of freedom (df), the Tucker-Lewis Index (TLI), the comparative fit index (CFI), the root mean square error of approximation (RMSEA) with a 90% confidence interval, and the standardised root mean square residual (SRMR) (Kline, 2016). The coefficient of determination (R^2) was used to measure the explained variance of the endogenous variables. We applied the Maximum Likelihood estimation routine (Byrne, 2010).

4. RESULTS

4.1. Descriptive statistics

The overall sample consisted of 251 respondents who were responsible for farm's decisions (78% always, 14% often, and 8% sometimes). Most respondents were male (92%), had completed upper secondary education (53%), had an average age of 53 years, and a median of 30 years of experience in the agricultural sector (Table 1). Most farms were located in southern Italy and on the islands (51.4), had a median utilised agricultural area (UAA) of 15 ha, employed less than 10 people (68%), with a median turnover of €200.000. The most frequently cultivated vegetables were tomatoes, both for fresh consumption (44%) and for the processing industry (41%), followed by peppers (16%) and zucchinis (11%).

Most of the sampled farmers had not yet adopted any of the proposed technologies (n=175, 69.7%). Those who have deployed any of these technologies relied on Level 1 (i.e. soil moisture sensors, n=43, 17.1%), and a few were already using automated irrigation systems (Level 2) or predictive models (Level 3), accounting for 6.4% (n=16) and 6.8% (n=17) respectively (Table 1). In light of these findings, it is important to understand the motivation for the adoption of new technologies and the factors that hamper their introduction.

Overall, the results in Table 2 show a moderately positive perceived usefulness of water-smart agricultural new technologies (mean score: 4.81), which means in particular that farmers moderately agree that by using this technology they could reduce water consumption and improve productivity. The results also show a moderately positive perceived ease of use (4.69) and output quality (4.59). Furthermore, important others had no significant influence (3.63), and there was relatively low anxiety about applying new technologies (3.16). The results indicated a positive evaluation of the sustainability aspects related to the new technology (e.g., reduced water consumption, enhanced technical skills, etc., mean score: 5.03), as well as positive technology self-efficacy (5.12). In particular, respondents stated that they would

Table 1. Description of the sample: farm characteristics and socio-demographic data of farmers (n=251).

Variables	Sample N	Sample %
Age of the respondent		
Age (years, mean and SD)	52.8 (11.9)	
Gender		
Male	231	92.0
Female	20	8.0
Others or prefer not to answer	0	0.0
Educational level		
Primary	8	3.2
Secondary lower	57	22.7
Secondary higher	132	52.6
Tertiary	54	21.5
Geographical area of the farm		
North-West	28	11.2
North-East	66	26.3
Center	28	11.2
South and Islands	129	51.4
Farm size		
UAA (ha, median and IQR)	15.0 (4.0-60.0)	
Farms by UAA classes		
< 2 ha	20	8.0
2 – 4.99 ha	47	18.7
5 – 19.99 ha	69	27.5
20 – 49.99 ha	45	17.9
> 50 ha	70	27.9

Variables	Sample N	Sample %
Most cultivated vegetables		
Tomato (for fresh consumption)	110	43.8
Tomato (for the processed industry)	104	41.4
Peppers	40	15.9
Zucchinis	27	10.8
Eggplants	13	5.2
Lettuce	13	5.2
Potatoes	12	4.8
Melons	9	3.6
Cauliflowers	8	3.2
Enterprise n. employee category		
Micro (1-9 employees)	171	68.1
Small (10-49)	64	25.5
Medium 1 (50-99)	12	4.8
Medium 2 (100-249)	4	1.6
Large (≥250)	0	0.0
Farm's turnover		
Turnover (.000 euro, median and IQR)	200 (90-650)	
Farmer's years of experience in agriculture		
Years of experience (median and IQR)	30 (20-40)	
Levels of water-smart technologies [a]		
No technological innovation	175	69.7
Level 1	43	17.1
Level 2	16	6.4
Level 3	17	6.8

Notes: Data are presented as the mean (SD) for continuous variables for which the hypothesis of normal distribution cannot be rejected at p<0.05, as median (IQR) otherwise, or as number (%) for nominal variables. SD = Standard Deviation. IQR = Interquartile Range. UAA = Utilised Agricultural Area. [a] Levels of water-smart technologies: Level 1) – soil moisture sensors, Level 2) – a system combining sensors with an automatic irrigation system, and Level 3) – sensors connected to an automated system, which in turn is connected to and interacts with predictive models.

use this innovation easily if they had technical support. Furthermore, consumers exhibited a moderately positive intention to adopt innovative water-smart agricultural technologies (4.58).

4.2. Drivers of digital innovation

Table 2 shows the descriptive statistics of the latent and observable variables, as well as the tests conducted on the constructs. The factor loadings of the variable items (λ) exceeded 0.50, the Cronbach's α and CR values were above 0.70, and the AVE values exceeded 0.50; these results, with the only exception of perceived ease of use, demonstrated strong reliability, as well as convergent and discriminant validity of all factors in the measurement model. Discriminant validity was further confirmed by verifying that the square root of the AVE for each construct, as shown in Table 3, was greater than the correlations between the constructs (Bagozzi and Yi, 2012).

Model 1 showed a good fit with the collected data: χ^2 (df) = 461.975 (280), CFI = 0.950, RMSEA = 0.051 (90%CI 0.043 – 0.059), TLI = 0.942 and SRMR = 0.054. The standardized path coefficients and their significance levels are shown in Table 4, whereas the unstandardized coefficients and standard errors are shown in the Appendix Table A2.

Overall, the model shows R^2 values of 0.65 for the intention and 0.16 for the behaviour in adopting a new water-smart technology. This means that, respectively, 65.1% of the variance in intention and 16.4% of the variance in behaviour can be explained by the tested variables. The results suggest that the intention to adopt an innovative water-smart technology significantly influences the actual behaviour (i.e., the adoption of the technology itself), as postulated by H6 (p<0.001). Behavioural

Table 2. Mean values (standard deviation, SD) and median values (interquartile range, IQR) of single items and constructs, factor loadings (λ), composite reliability (CR), average variance extracted (AVE) and Cronbach's α of the sample (n=251).

	Mean (SD)	Median (IQR)	λ	CR	AVE	α
Perceived Usefulness	4.81 (1.06)	5.00 (4.25-5.25)		0.84	0.56	0.84
PU1	4.80 (1.25)	5.00 (4.00-5.00)	0.78			
PU2	4.61 (1.34)	5.00 (4.00-5.00)	0.75			
PU3	4.86 (1.20)	5.00 (4.00-5.00)	0.79			
PU4	4.95 (1.37)	5.00 (4.00-6.00)	0.67			
Perceived Ease of Use	4.69 (0.92)	4.50 (4.00-5.00)		0.61	0.45	0.61
PEU1	4.98 (1.06)	5.00 (4.00-5.00)	0.59			
PEU2	4.40 (1.10)	5.00 (3.00-5.00)	0.75			
Output Quality	4.59 (0.98)	4.75 (4.00-5.00)		0.83	0.56	0.84
OQ1	4.57 (1.15)	5.00 (4.00-5.00)	0.70			
OQ2	4.52 (1.25)	5.00 (4.00-5.00)	0.78			
OQ3	4.80 (1.16)	5.00 (4.00-5.00)	0.85			
OQ4	4.48 (1.20)	5.00 (4.00-5.00)	0.64			
SAFA	5.03 (1.00)	5.00 (4.67-5.67)		0.78	0.55	0.79
SAFA1	5.12 (1.21)	5.00 (5.00-6.00)	0.68			
SAFA2	4.87 (1.17)	5.00 (4.00-5.00)	0.72			
SAFA3	5.10 (1.20)	5.00 (5.00-6.00)	0.81			
Anxiety	3.16 (1.18)	3.00 (2.67-3.67)		0.85	0.66	0.85
ANX1	3.28 (1.33)	3.00 (3.00-4.00)	0.74			
ANX2	3.10 (1.33)	3.00 (2.00-3.00)	0.88			
ANX3	3.10 (1.37)	3.00 (2.00-3.00)	0.81			
Technology Self-Efficacy	5.12 (1.11)	5.00 (4.67-6.00)		0.92	0.80	0.92
TSE1	5.07 (1.22)	5.00 (5.00-6.00)	0.87			
TSE2	5.20 (1.18)	5.00 (5.00-6.00)	0.93			
TSE3	5.08 (1.18)	5.00 (5.00-6.00)	0.88			
Subjective Norms	3.63 (1.09)	3.67 (3.00-4.33)		0.76	0.53	0.74
SN1	3.84 (1.31)	4.00 (3.00-5.00)	0.84			
SN2	3.52 (1.41)	3.00 (3.00-5.00)	0.51			
SN3	3.53 (1.31)	3.00 (3.00-5.00)	0.78			
Behavioural Intention	4.58 (1.35)	4.67 (4.00-5.33)		0.91	0.77	0.91
BI1	4.41 (1.51)	5.00 (4.00-5.00)	0.93			
BI2	4.54 (1.47)	5.00 (4.00-5.00)	0.89			
BI3	4.80 (1.41)	5.00 (4.00-6.00)	0.80			
Behaviour [a]	1.50 (0.89)	1.00 (1.00-2.00)				

Note: All items were measured on a 7-point scale (from 'strongly disagree' to 'strongly agree'). [a] Behaviour was assessed with a single item, ranging from 1 to 4, considering the different adoption levels (1=No technological innovation; 2=Level 1; 3=Level 2; 4=Level 3).

intention, in turn, is positively influenced by perceived usefulness with $p<0.001$, which is one of the two core variables of the TAM3 (H4 accepted).

Perceived ease of use does not significantly affect the intention to adopt technologies, therefore not supporting H3a; however, it positively affects perceived usefulness of new technologies with $p<0.05$, confirming H3b. H5 is also supported since subjective norm has a positive effect on the intention to adopt a technology ($p<0.001$), showing that perceived social pressure has an influence on the farmers' motivation to adopt a new technology. The construct of anxiety shows a negative effect on the perceived ease of use ($p<0.05$), a property that is stimulating and that could open up new ways of designing and conceptualizing modern technologies. Perceived ease of use, on the other hand, is positively influenced by the self-efficacy of the technology, with $p<0.001$. In turn, perceived usefulness is influenced by the quality of the output (i.e., the perceived quality of the effects achieved by using the technology, $p<0.001$) and by the SAFA-based items ($p<0.05$).

Table 3. Spearman's rank-order correlations (ρ) between the constructs including the squared root of the AVE of each construct (reported in bold on the main diagonal).

	PU	PEU	OQ	SAFA	ANX	TSE	SN	BI	BEH
PU	0.75	0.31***	0.63***	0.52***	-0.28***	0.40***	0.36***	0.57***	0.36***
PEU		0.67	0.24***	0.31***	-0.17**	0.34***	0.14*	0.28***	0.15*
OQ			0.75	0.46***	-0.21***	0.34***	0.43***	0.60***	0.35***
SAFA				0.74	-0.23***	0.63***	0.16*	0.39***	0.19**
ANX					0.81	0.16**	-0.15*	-0.29***	0.17**
TSE						0.89	n.s.	0.39***	n.s.
SN							0.73	0.44***	0.36***
BI								0.88	0.40***

Note: PU = Perceived Usefulness; PEU = Perceived Ease of Use; OQ = Output Quality; SAFA = Sustainability Assessment of Food and Agriculture Systems; ANX = Anxiety; TSE = Technology Self-Efficacy; SN = subjective norms; BI = Behavioural Intentions; BEH = behaviour; Sign.: *** p<0.001, ** p<0.01, * p<0.01, n.s. = not significant.

Table 4. TAM3-extended model: coefficient of determination (R^2), standardised coefficients (β), p-values, and research hypotheses (n=251).

	Model 1				Model 2			
	R^2	β	p	Hypotheses	R^2	β	p	Hypotheses
PU	0.791				0.811			
PEU → PU		0.133	0.044	H3b accepted		0.118	0.068	H3b accepted
OQ → PU		0.658	<0.001	H1a accepted		0.693	<0.001	H1a accepted
SAFA → PU		0.199	0.027	H1b accepted		0.172	0.052	H1b accepted
SN → PU		0.045	0.512	H1c rejected		0.033	0.627	H1c rejected
EMP → PU						0.157	<0.001	
PEU	0.305				0.302			
TSE → PEU		0.487	<0.001	H2a accepted		0.488	<0.001	H2a accepted
ANX → PEU		–0.169	0.041	H2b accepted		–0.161	0.051	H2b accepted
BI	0.651				0.653			
PU → BI		0.601	<0.001	H4 accepted		0.616	<0.001	H4 accepted
PEU → BI		0.069	0.295	H3a rejected		0.056	0.380	H3a rejected
SN → BI		0.278	<0.001	H5 accepted		0.261	<0.001	H5 accepted
UAA → BI						0.081	0.068	
BEH	0.164				0.178			
BI → BEH		0.404	<0.001	H6 accepted		0.376	<0.001	H6 accepted
UAA → BEH						0.158	0.006	
Model fit indices								
χ^2 (df)	461.975 (280)				510.533 (328)			
CFI	0.950				0.950			
TLI	0.942				0.943			
RMSEA (90% C.I.)	0.051 (0.043 – 0.059)				0.047 (0.039 – 0.055)			
SRMR	0.054				0.062			

Note: PU = Perceived Usefulness; PEU = Perceived Ease of Use; OQ = Output Quality; SAFA = Sustainability Assessment of Food and Agriculture Systems; ANX = Anxiety; TSE = Technology Self-Efficacy; SN = subjective norms; BI = Behavioural Intentions; EMP = number of employees; UAA = average farm size (Utilised agricultural area); BEH = Behaviour.

When controlling for individual and organizational factors we have found that, among all observed items, only the average farm size (expressed in hectares of utilised agricultural area, UAA) and the number of employees have an effect on the endogenous variables. In particular, the number of employees positively influences respondents' perceived usefulness ($p<0.001$), indicating that decision-makers in larger farms, in terms of workforce, find the innovative technology capable of enhancing farm performance. In turn, the average farm size in UAA positively influences the behaviour ($p<0.001$) and behavioural intentions ($p<0.10$). In other words, respondents working in larger farms are more willing to adopt the new technologies, or have already adopted them. Overall, the Model 2 shows good fit with the data (χ^2 (df) = 510.533 (328), CFI = 0.950, RMSEA = 0.047 (90%CI 0.039 – 0.055), TLI = 0.943 and SRMR = 0.062) while also improving the explained variance of behaviour, up to 17.8%. The overall path and the tested hypotheses are confirmed, albeit with some of them showing slightly lower significance levels (Table 4).

5. DISCUSSION

Our study found that approximately 70% of the farmers interviewed did not adopt any of the proposed digital technologies. This finding confirms the limited adoption of innovative water-smart solutions in the Italian horticultural sector, highlighting the need to thoroughly understand the barriers and the factors that could promote such adoption. Therefore, the results of this study represent an important step toward achieving this goal. The applied extended-TAM3 model consistently explains around 18% of the variance in the behaviour (the adoption of water-smart technologies), and 65% of the variance in individuals' intention to adopt the new digital technologies. We confirm that behavioural intention is a significant predictor of the behaviour, indicating that farmers motivation in adopting the innovative technologies affect the actual adoption. The applied model further assumes that the effect of other variables (e.g., self-efficacy) on behavioural intention is mediated by perceived usefulness and perceived ease of use. The findings are consistent with previous literature, particularly in relation to the importance of perceived usefulness (Davis, 1989; Venkatesh and Davis, 2000). Perceived usefulness was found to be a strong determinant of farmers' intention to adopt new water-smart technologies, highlighting its role in shaping the adoption behaviour. Other studies conducted using TAM demonstrate that perceived usefulness is a central aspect for technology adoption, provided that it do not cause a significant increase in the production costs (Pierpaoli et al., 2013). This supports the findings of Paustian and Theuvsen (2017) and Shang et al. (2021), who emphasize the importance of clear and tangible benefits for adoption of technologies in agriculture.

However, our results differ from the TAM3 model with respect to the role of perceived ease of use, which has no influence on adoption intentions. While TAM3 suggests that perceived ease of use is an important determinant (Venkatesh and Bala, 2008), the limited impact observed can be attributed to contextual factors, such as the different levels of digital literacy and prior experience with technology among Italian farmers. The not significant effect of this factor was also found in another studies (for a review, see Osrof et al., 2023). In another study carried out in the Italian fruit and grapevine sector, perceived ease of use was found to be insignificant when adopting variable rate irrigation (Canavari et al., 2021). Schulze Schwering et al. (2022) also found that perceived ease of use may become less important when end users rely more on external support or community recommendations, as social norms take precedence.

Social norms were another important factor that positively influenced adoption intentions in our study, which is consistent with the findings of Senyolo et al. (2018). The role of perceived social pressure in motivating farmers suggests that fostering a culture of innovation and demonstrating success among peers may be critical to increasing adoption rates. Furthermore, our findings echo the observations of Dissanayake et al. (2022) that contextual and cultural factors play a significant role in shaping individuals' intention to adopt innovative technologies.

By demonstrating that sustainability-related factors, such as improved water management and workforce skills, influence perceived usefulness, our study confirms the potential of sustainability considerations to improve technology uptake. This result is in line with the research findings of Montes de Oca Munguia et al. (2021), who advocate the inclusion of sustainability goals in the technology adoption framework. This last point is thought-provoking when it comes to examining the role of farmers and their commitment to sustainability, as well as their awareness of the use of smart devices to promote more sustainable practices. In the face of climate change and the pressure that agriculture is putting on environmental resources, only the direct and committed involvement of farmers can promote a more conscious and widespread use of smart technologies with the aim of reaping their benefits (Menozzi et al., 2015). Furthermore, linking sustainability aspects to the concept of usefulness could also promote higher acceptance and adoption rate, which underpins the positive impact for farmers in terms of profitability. This is also confirmed by the correlation indices between the SAFA-inspired construct and the technology self-efficacy and output quality constructs, that are both high and significant, 0.74 and 0.70 respectively.

Technology self-efficacy strongly affects perceived ease of use, indicating that individuals who are more confident in their ability to use the technology are more likely to perceive it as an easy task. In other studies, perceived behavioural control has been found to predict intentions to adopt agricultural sustainability schemes (Menozzi et al., 2015). On the other hand, our results also suggest barriers to adoption, including lack of digital skills and limited access to information, which is consistent with the observations of other studies (Osrof et al., 2023; Sabbagh and Gutierrez, 2023; Yigezu et al., 2018). To address these barriers, targeted training programs and policies are needed to lower the entry threshold for farmers, especially for farmers in resource-poor regions. Interestingly, the negative correlation between anxiety and perceived ease of use highlights the importance of developing technologies that minimize cognitive and operational barriers. In our study, we controlled the endogenous variables of the model (i.e., perceived usefulness, perceived ease of use, intention to adopt, and behaviour) with individual and organizational factors. Only farm size and number of employees had a significant effect on these variables, while the other constructs showed no significant effect. Another review revealed that several of these factors showed inconsistencies across multiple studies (Osrof et al., 2023). For instance, the insignificance effect of farmers' level of education on decision-making could be explained by the possibility that highly educated farmers might opt for careers outside farming (Michels et al., 2020) or show interest in basic technology features that do not require extensive education (Wachenheim et al., 2021). Similarly, although numerous studies have found that older farmers are less motivated to adopt smart technologies on their farms, Osrof et al. (2023) identified a large number studies with inconsistent results, where age did not affect farmers' adoption decisions. For example, age did not influence farmers' intention to use smart technologies such as yield monitors with GPS (García-Jiménez et al., 2022). Farm location is also a notable barrier that might hamper the adoption of smart technologies, in particular if farms face unfavourable conditions such as climate, rainfall, or poor soil quality (Osrof et al., 2023; Paxton et al., 2011). However, in our case farm location did not significantly affect the endogenous variables, as other factors associated with this variable (e.g., farm size) likely masked this effect.

On the contrary, our study indicated that larger farms, in terms of UAA acreage, are more likely to be motivated to adopt the innovative water-smart technologies or have already adopted them. This finding confirms that larger farm size is consistently seen as pivotal for achieving economies of scale when adopting smart technologies that entail high investments and initial costs (Osrof et al., 2023).

The significant effect of the number of employees on the perceived benefit indicates that farms with a large workforce are more likely to believe that the use of water-saving technologies will improve their performance. This result can be interpreted in different ways. On the one hand, it could indicate that the use of these technologies could reduce the need for farm labour and thus reduce labour costs. On the other hand, it could indicate that these technologies are perceived to improve the knowledge and technical skills of employees and thus increase the productivity of the workforce. This second interpretation seems more consistent with the positive effect of the SAFA-based construct on perceived usefulness.

In summary, this study enriches the understanding of technology adoption in agriculture by confirming the relevance of the key TAM3 constructs and also highlighting context-specific variations. By addressing the identified barriers and harnessing the drivers of adoption, policy makers, technology developers and stakeholders can promote greater technology adoption and thus contribute to more sustainable and efficient agricultural practices.

6. CONCLUSION

The integration of digital technologies in the Italian horticultural sector is a multifaceted challenge influenced by a variety of individual, technological, social and contextual factors. This study shows that individual intention is an important determinant of the actual adoption of innovative water-saving technologies and highlights the crucial role of farmer motivation in decision-making. Perceived usefulness of these technologies has a significant effect on adoption intention, while perceived ease of use requires further investigation due to its limited relevance in the current context. Social norms were identified as an important determinant of farmers' intentions, highlighting the importance of community influence and external support in promoting the adoption of digital technologies. To close the observed adoption gap, targeted interventions should be developed to address barriers such as digital literacy, infrastructure and accessibility of technology. Furthermore, the regional and culture-specific nuances observed in this study should be taken into account when developing customised strategies.

The results highlight important policy and business implications, suggesting that government agencies, agricultural cooperatives, and technology developers should emphasize the economic and environmental benefits of digital irrigation technologies. Encouraging farmer networks and knowledge-sharing initiatives could also accelerate adoption. By addressing these research gaps, this study contributes to both the academic literature and practical policy making. It provides a refined theoretical model to understand technology adoption in small- and medium-sized farms and offers practical insights to promote sustainable and efficient water management in agriculture. Further exploration of constructs that have negative correlates, such as anxiety, could lead to more user-centred technology design that reduces barriers to technology adoption and improves usability.

Some limitations of this study should be mentioned. The study reflects not only a specific context, such as the horticultural sector, but also national characteristics, which can vary greatly from country to country due to different regulatory and incentive frameworks, cultural practises and, most importantly, technological infrastructures. Nevertheless, the sample is not representative of Italian farmers. This must be taken into account when interpreting the results and deriving consequences for corporate management. An extension of the sample and a repetition of the study in other countries could therefore be interesting to test the validity of all the hypotheses put forward in the original theory. Second, we did not consider prospective behaviour, i.e., we did not measure actual behaviour in the future (i.e., future adoption of the innovative technologies), but only current behaviour. Although this approach is quite common in similar studies, it might have limited the compatibility of behaviour with its antecedents (McEachan et al., 2011). Moreover, this study used self-report measures about the behaviour which may be subject to response biases. However, the CATI method can help with complex or sensitive questions by allowing the interviewer to clarify questions and guide the respondent, thus reducing misinterpretation and encouraging more accurate responses (Dillman et al., 2014).

Despite these limitations, this study is, to our knowledge, one of the first aimed at investigating the relative importance of behavioural precursors in explaining the intention to adopt innovative water-smart technologies in Italian horticultural farms.

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APPENDICES

Table A1. Constructs and Items.

Codes	Items
	Perceived Usefulness
PU1	This innovation would make my work easier
PU2	This technology would make my work faster
PU3	This innovation could improve my productivity
PU4	By using this technology, I could reduce water consumption in my company
	Perceived Ease of Use
PEU1	This technology should be easy to use
PEU2	Using this technology will not require much effort
	Output Quality
OQ1	I expect that the results of using this technology will be excellent
OQ2	Using this technology will improve the quality of my products
OQ3	By using this system, I would increase the efficiency of my work
OQ4	By using this innovation, I would increase the quantity of product in the field
	SAFA
SAFA1	By using this innovation, I could help reduce water consumption
SAFA2	With the introduction of this technology, employees could receive training and enhance their knowledge and technical skills
SAFA3	By introducing this innovation, I could receive training and improve my technical skills
	Anxiety
ANX1	I get nervous when working with new technologies
ANX2	New technologies make me feel uncomfortable
ANX3	I am afraid of applying new technologies
	Technology Self-Efficacy
TSE1	I would use this technology easily if someone showed me how to use it
TSE2	I would use this innovation easily if I had technical support
TSE3	I would use this innovation easily if I were familiar with the system
	Subjective Norms
SN1	People whose opinions matter to me think that I should use this technology
SN2	Many producers I know have already adopted this innovation
SN3	My customers think that I should use this technology
	Behavioural Intention
BI1	I will definitely use this technology in the near future
BI2	I intend to use this technology in the near future
BI3	If there were no significant barriers, I would use this system in the near future

Note: All items were measured on a 7-point scale (from ‘strongly disagree’ to ‘strongly agree’).

Table A2. TAM3-extended model: unstandardized beta coefficients and standard errors (S.E.) (n=251).

	Model 1		Model 2	
	Beta	S.E.	Beta	S.E.
PU				
PEU → PU	0.202*	0.100	0.176#	0.097
OQ → PU	0.796***	0.136	0.824***	0.134
SAFA → PU	0.236*	0.106	0.200#	0.103
SN → PU	0.040	0.060	0.028	0.059
EMP → PU			0.249***	0.068
PEU				
TSE → PEU	0.308***	0.064	0.307***	0.064
ANX → PEU	-0.098*	0.048	-0.093#	0.047
BI				
PU → BI	0.862***	0.110	0.890***	0.110
PEU → BI	0.149	0.142	0.121	0.138
SN → BI	0.351***	0.082	0.324***	0.080
UAA → BI			0.000#	0.000
BEH				
BI → BEH	0.256***	0.039	0.240***	0.039
UAA → BEH			0.000**	0.000

Note: PU = Perceived Usefulness; PEU = Perceived Ease of Use; OQ = Output Quality; SAFA = Sustainability Assessment of Food and Agriculture Systems; ANX = Anxiety; TSE = Technology Self-Efficacy; SN = subjective norms; BI = Behavioural Intentions; EMP = number of employees; UAA = average farm size (Utilised agricultural area); BEH = Behaviour. Sign.: *** p<0.001, ** p<0.01, ** p<0.05, # p < 0.10.

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Farmers' intention to use Agriculture 4.0 in marginal and non-marginal conditions

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Abstract. Agriculture 4.0 enhances efficiency, sustainability, and yields while supporting climate change mitigation and adaptation. This study explores the adoption of Agriculture 4.0 among 131 durum wheat farmers in Sardinia, focusing on differences between marginal and non-marginal areas. Using an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) framework, which includes perceived performance risk, the study identifies key factors influencing adoption. Facilitating conditions positively impact the adoption intentions, and perceived performance risk has a negative impact. However, performance expectancy, effort expectancy, social influence and price value don't significantly affect adoption intentions. Policy recommendations include financial support, technical advice access, training programs, and awareness campaigns to promote adoption. These interventions aim to address barriers and foster equitable integration of Agriculture 4.0 technologies across diverse farming contexts.

Keywords: Agriculture 4.0, technology adoption, marginal areas, non-marginal areas, UTAUT2.

1. INTRODUCTION

Marginal areas are territories where farming is challenging due to a confluence of biophysical, socioeconomic, and infrastructural aspects (Ahmadzai et al., 2021; Alhajj Ali et al., 2024; Peter et al., 2018; Sallustio et al., 2018). These territories face natural and geographic constraints that reduce agricultural competitiveness (Ahmadzai et al., 2022; Csikós & Tóth, 2023; Food & Nations, 2017; Jussila et al., 2019; Lal, 2004). On the other hand, non-marginal areas benefit from better natural resources, more established infrastructure, and more access to markets, technology, and research and development (R&D) (Coxhead et al., 2002; Hidayat et al., 2024; Rondinelli, 1992; Ruddle, 1991). These areas are often better integrated into regional, national, and worldwide agricultural markets, resulting in increased production and economic benefits (Hidayat et al., 2024; Jouanjean, 2013; Long et al., 2016).

Farmers in non-marginal areas are generally more willing to accept new technologies due to improved access to credit and extension services, which reduce perceived risks and increase the possibility of successful adoption

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(Pannell et al., 2006; Rogers, 2003; Yigezu et al., 2018). Differently, farmers in marginal areas are more likely to be risk-averse and hesitant to adopt new technologies due to uncertainties about their effectiveness and the potential financial risks involved (Girma et al., 2023; Marra et al., 2003; Wu et al., 2023). These farmers may also lack the technical knowledge and skills required to effectively implement and benefit from new technologies, as well as the necessary support systems for ongoing innovation and R&D (Abrol & Ramani, 2014; Douthwaite et al., 2001; Klerkx et al., 2019; Scoones et al., 2009). Agriculture 4.0 may provide a transformative opportunity to solve these imbalances. Agriculture 4.0, an advanced framework that incorporates technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), robotics, precision farming, and big data analytics, has the potential to transform farming methods in a variety of situations (Abiri et al., 2023; Fuentes-Peñailillo et al., 2024; Raj et al., 2021; Stupina et al., 2021; Wolfert et al., 2017). IoT systems enable real-time monitoring of soil, crops, and equipment (e.g., moisture sensors and smart irrigation) (Osservatori.net, 2023). Precision agriculture tools such as GPS-guided machinery and variable-rate technology (VRT) optimize the use of inputs like fertilizers, pesticides, and water (McCormick, 2023) being tools to achieve more sustainable farming systems. Remote sensing technologies and drones are destinated to crop health analysis and yield forecasting (Maffezzoli et al., 2022). Robotics and automation through autonomous tractors, harvesters, and weeding robots help reduce labor requirements (McCormick, 2023; Osservatori.net, 2023) , while AI and machine learning offer predictive analytics and decision support (Abiri et al., 2023). Additionally, blockchain and cloud computing enhance traceability and data management, big data analytics support informed forecasting and strategic planning (Maffezzoli et al., 2022), and mobile applications provide farmers with access to weather data, technical assistance, and real-time market prices (AgendaDigitale, 2023). Together, these technologies not only improve efficiency and productivity but also reduce environmental impact and enhance climate resilience. These advances are intended to maximize resource utilization, boost crop yields, and improve overall farm management, being extremely advantageous, especially in marginal areas (Abiri et al., 2023; Benfica et al., 2023; Klerkx et al., 2019; Rose & Chilvers, 2018; Saidakhmedovich et al., 2024). However, whereas non-marginal areas are well-positioned to adopt these technologies, marginal areas face major barriers (Benfica et al., 2023; Klerkx et al., 2019; Mercure et al., 2021; Saidakhmedovich et al., 2024). Understanding these constraints is critical to ensure that the benefits of Agriculture 4.0 are more widely realized, thereby possibly bridging the development gap between marginal and non-marginal areas (Burland & von Cossel, 2023; Kirk & Cradock-Henry, 2022; Sureth et al., 2023). A complex interaction of elements such as economic situations, information access, social influences, and individual perceptions of risk and benefit impact farmers' attitudes and behaviours regarding new technology adoption (Adrian et al., 2005; Brick & Visser, 2015; Rizzo et al., 2024; Sabbagh & Gutierrez, 2022, 2023). Previous studies investigated such elements on smart agriculture technologies in the Italian context (Caffaro & Cavallo, 2019; Caffaro et al., 2020; Caffaro et al., 2019).

To investigate these dynamics,this research utilized the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model (Venkatesh et al., 2012), which provides a comprehensive framework for understanding technology adoption (Alghatrifi & Khalid, 2019; Macedo, 2017; Tamilmani et al., 2021).

UTAUT2 expands on the original UTAUT model, which identifies core factors that influence technology acceptance and use (Chang, 2012; Venkatesh et al., 2012). UTAUT2 introduces additional variables such as hedonic motivation, price value, and habit that capture a more comprehensive understanding of consumer and user behaviour in different contexts such as mobile applications, digital communication, e-health, educational tools, banking, agriculture, etc. (An et al., 2016; Arain et al., 2019; Arenas Gaitán et al., 2015; Chang, 2012; Medeiros et al., 2022; Venkatesh et al., 2012; Widodo et al., 2019). As well, UTAUT2 is important in understanding technology adoption since it explains both short-term and long-term technology use (Diekmann & Theuvsen, 2019). Moreover, research has shown that perceived performance risk predicts the intention to adopt a new technology (Abikari, 2024; Budhi & Aminah, 2010; Budhi et al., 2022; Deng et al., 2018; Diekmann & Theuvsen, 2019; Hasselwander & Weiss, 2024; Sohn, 2024). For this reason, we extended the UTAUT2 model to include the variable of perceived performance risk (Featherman & Pavlou, 2003).

We focus our analysis on durum wheat farmers in the Sardinia region, considering both marginal and non-marginal conditions. Sardinia's unique agricultural landscape, with considerable regional differences, makes it an appropriate case study for investigating these dynamics. Some areas of Sardinia suffer severe challenges due to low soil quality, water scarcity, and limited infrastructure (Fraser-Baxter, 2024). Durum wheat, a key crop in the region and vital to producing traditional items such as pasta and bread, is inseparably linked to Sardinian history and the local economy (Mefleh et al., 2019; Soddu et al., 2013). Furthermore, durum wheat agriculture in Sardinia is particularly sensitive to environmental conditions, making it a great indicator of the overall agricultural issues faced across the region (Mereu, 2010).

Agriculture 4.0 technologies may improve durum wheat sowing, monitor soil moisture and nutrient levels in real time, and predict crop diseases before they spread (Balyan et al., 2024; Güven et al., 2023; Shafi et al., 2019; Trivelli et al., 2019). The geographical differences in durum wheat yields in Sardinia, caused by different soil quality, water availability, and infrastructure, make it a suitable case study for investigating farmers' intentions to implement Agriculture 4.0 technologies in marginal and non-marginal areas.

This study is pioneering in proposing an expanded UTAUT2 model to explore the behavioural factors influencing the adoption of Agriculture 4.0 technologies in marginal and non-marginal settings. The implications of this study may extend beyond Sardinia, providing significant insights into the broader challenges and opportunities associated with the adoption of agricultural technologies. The findings could help shape agricultural policies that promote sustainable farming practices and economic development in locations with similar agricultural profiles. Moreover, it intends to contribute to the global discourse on sustainable agricultural innovation by offering a detailed knowledge of the factors that influence technology adoption, thereby assisting in the transition to more resilient and efficient farming systems. This leads to the central research question: "*What are the key factors influencing farmers' behavioural intention to adopt Agriculture 4.0 technologies in Sardinia?*"

This research aligns with several United Nations Sustainable Development Goals (SDGs), specifically SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production). By investigating the behavioural and structural factors that influence the adoption of Agriculture 4.0 technologies, especially in marginal areas, the study contributes to the broader agenda of building resilient food systems and fostering inclusive and sustainable economic growth in rural areas (SDG 8). Moreover, promoting the use of resource-efficient technologies directly supports climate action goals (SDG 13) by reducing environmental impact and improving adaptation to climate-related risks. This study contributes to the ongoing discussion on farmers' motivations and aspirations in agricultural innovation. As noted by Arata and Menozzi (2023), there is a need for multidimensional approaches that account for both individual drivers and contextual influences on farmer behaviour. While recent contributions, such as Deißler et al. (2022), have explored the role of personality traits in shaping aspirations in smallholder contexts, our work adds to this conversation by focusing on behavioural intentions toward Agriculture 4.0 use. By drawing on the Theory of Planned Behaviour, our approach emphasizes farmers' perceptions and attitudes as key drivers of decision-making. These are the factors that, while distinct from personality traits, are similarly influential in shaping future-oriented action. This alignment offers a complementary perspective to the journal's growing body of research on aspirations and innovation adoption. The paper is structured as follows: section 2 outlines the theoretical framework and hypotheses; section 3 details the methodology, including data collection and analysis methods; section 4 presents and discusses the results; section 5 provides conclusions, and section 6 addresses the study's limitations.

2. AGRICULTURE 4.0 AND BEHAVIOURAL MODELS FOR THE ADOPTION OF NEW TECHNOLOGIES

2.1. Agriculture 4.0 in marginal and non-marginal areas

Agriculture 4.0 represents a transformative shift in farming, leveraging advanced technologies such as precision agriculture, IoT, AI, robotics, and big data analytics to enhance efficiency, optimize resource use, and foster sustainable agricultural practices (Abiri et al., 2023; Wolfert et al., 2017). These technologies have the potential to revolutionize farming in both marginal and non-marginal areas, but their adoption and impact vary significantly due to differences in infrastructure, access to resources, and socioeconomic conditions between the two regions (Ahmadzai et al., 2022; Klerkx et al., 2019). Non-marginal regions often benefit from stable and predictable weather patterns, ensuring that Agriculture 4.0 technologies can function optimally (Mana et al., 2024; Pechlivani et al., 2023). These tools, which include IoT sensors that monitor crop health, soil moisture levels, and pest infestations, empower farmers to make data-driven decisions that enhance productivity, reduce resource consumption, and promote environmental sustainability (Fuentes-Peñailillo et al., 2024; Raj et al., 2021). The availability of advanced farming machinery and technologies, such as AI-driven machinery and variable rate technology (VRT), further contributes to higher productivity, with less environmental impact (Shafi et al., 2019; Van Klompenburg et al., 2020).

On the other hand, marginal areas face a host of challenges that hinder the adoption of Agriculture 4.0 technologies. Marginal areas are often characterized by poor soil quality, limited water resources, geographical isolation, and inadequate infrastructure, which restrict the applicability of advanced farming technologies (Ahmadzai et al., 2021; Jacobs et al., 2022). These regions are prone to extreme environmental conditions such as drought, floods, heat waves, soil erosion and water scarcity, making it difficult to implement technologies like precision irrigation or smart farming systems that rely on consistent environmental data (Akter et al., 2023; Cogato et al., 2019; Wheaton & Kulshreshtha, 2017). The absence of digital literacy and technical support networks in these regions makes it even more challenging for farmers to adopt new technologies (Dibbern et al., 2024; Ruzzante et al., 2021). As a result, farmers in these areas often lack the knowledge or resources to implement technologies such as IoT sensors, AI-driven machinery, and other forms of Agriculture 4.0 (Douthwaite et al., 2001; Klerkx et al., 2019).

Additionally, the high cost of adopting advanced technologies further exacerbates the divide between marginal and non-marginal areas. While financial support mechanisms such as subsidies and loans are more readily available in non-marginal areas, farmers in marginal regions often have limited access to credit and financial resources, making it difficult for them to invest in expensive technologies like artificial intelligence (AI) driven machinery or VRT (Klerkx et al., 2019; Yigezu et al., 2018). In marginal areas, where the financial risks of farming are already high due to environmental unpredictability, the upfront investment in advanced technologies can seem discouraging (Hurlbert et al., 2019; Khan et al., 2024). Without sufficient financial backing, many farmers prioritize short-term survival, limiting their ability to make long-term investments in precision farming tools that could potentially enhance productivity (Marra et al., 2003).

Environmental factors, including the vulnerability to climate change, further differentiate the two regions in terms of Agriculture 4.0 adoption. In non-marginal areas, stable climatic conditions, fertile soils, and reliable access to water resources make it easier to deploy Agriculture 4.0 (Javaid et al., 2022; Solaw, 2011). Technologies that rely on real-time data on soil moisture and weather conditions can significantly enhance water use efficiency and boost agricultural productivity (Balyan et al., 2024). However, marginal areas face more unpredictable environmental factors that challenge Agriculture 4.0. In these areas, the high variability of environmental conditions means that Agriculture 4.0 may not deliver accurate or effective results unless adapted specifically to local conditions (Jacobs et al., 2022).

Social and cultural factors also influence the adoption of Agriculture 4.0 technologies, with farmers in non-marginal areas typically more exposed to modern farming practices and educational programs (Ahmed & Ahmed, 2023; Nhuong & Truong, 2024). In these regions, farmers often have access to extension services, training programs, and education that promote the adoption of innovative technologies (Gardezi & Bronson, 2020; Raji et al., 2024; Ruzzante et al., 2021). Their more favourable attitudes towards technology adoption are often supported by governmental and institutional initiatives aimed at integrating new technologies into farming practices (Cramb, 2000; Tey & Brindal, 2012). In contrast, farmers in marginal areas may be more risk-averse, especially when their livelihoods are already precarious due to environmental and financial challenges (Scoones et al., 2009). The limited access to education, technical knowledge, and extension services in these regions further limits the willingness and ability of farmers to adopt new technologies, resulting in slower adoption rates compared to non-marginal areas (De Rosa & Chiappini, 2012; Girma et al., 2023; LEAP, 2023; Masi et al., 2023; Wu et al., 2023).

The differences in the adoption of Agriculture 4.0 technologies between marginal and non-marginal areas highlight the need for tailored interventions. While non-marginal areas focus on optimizing technology and fostering innovation, marginal areas require foundational efforts to improve basic infrastructure, enhance digital literacy, and address the specific environmental and socioeconomic challenges that hinder technology adoption (Elsawah et al., 2020; Loo et al., 2023; Mazzucato & Willetts, 2019). The development of affordable, locally tailored technologies and support systems is crucial for ensuring that farmers in marginal areas can benefit from the transformative potential of Agriculture 4.0, without exacerbating existing inequalities (Jacobs et al., 2022; Klerkx et al., 2019).

Agriculture 4.0 technologies present a stark contrast between marginal and non-marginal agricultural areas due to inherent disparities in natural resources, infrastructure, socioeconomic conditions, and access to technology (Ahmadzai et al., 2022; Klerkx et al., 2019; Saidakhmedovich et al., 2024). Understanding these contrasts is critical for developing strategies that ensure equitable access to these technologies and bridge the development gap.

2.2. The Unified Theory of Acceptance and Use of Technology 2

This study utilizes the UTAUT2 model to explore the factors affecting farmers' intentions to adopt Agriculture 4.0 technologies. The UTAUT2 model, introduced by Venkatesh et al. (2012), expands upon the original UTAUT framework by integrating additional constructs pertinent to consumer-related contexts. The original UTAUT model emerged from synthesizing eight theoretical frameworks from various disciplines, focusing on technological change and adoption.: Innovation Diffusion Theory IDT (Rogers, 1962); Theory of Reasoned Action TRA (Ajzen & Fishbein, 1980); Theory of Planned Behaviour TPB (Ajzen, 1991); Social Cognitive Theory SCT (Bandura, 1986); Technology Acceptance Model TAM (Davis, 1989); Model of PC Utilization MPCU (Thompson et al., 1991); Motivational Model MM (Davis et al., 1992); Combined TAM-TPB C-TAM (Taylor & Todd, 1995). The main value of this model arises from bringing a historical light on technology use by working around a set of constructs; that is, concepts that encapsulate what is central to the effects of technology use from a user's intention perspective (Yu, 2012). The UTAUT model centered on four constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) with moderating demographic inputs: gender, age, level of experience, and voluntariness of use (Venkatesh et al., 2003). Table 1 illustrates these constructs alongside their theoretical origins, showcasing how each is rooted in one or more of the eight foundational models. Building on the theoretical foundation of UTAUT, Venkatesh et al. (2012) introduced the UTAUT2 model, a pivotal framework that emphasizes the consumer perspective by incorporating three key factors: Hedonic Motivation, Price/Value, and Habit. This enhancement significantly boosts the model's predictive accuracy for estimating user adoption, reaching up to 74% (Venkatesh et al., 2016). The UTAUT2 model's applicability has been widely recognized as a robust framework within the technology industry. The extensive body of research supporting it underscores its effectiveness in analysing the adoption of new technologies, especially in diverse cultural and social contexts (Šumak & Šorgo, 2016). Several studies, such as those by Ena and Siewa (2022) Toral et al. (2018), have utilized the UTAUT2 model to investigate the factors influencing farmers' adoption of precision agriculture technologies.

Table 1. The main constructs of UTAUT and their origins.

Constructs	Variables	Model contributing to constructs
Performance Expectancy	Perceived usefulness	Technology Acceptance Model (TAM) (Davis, 1989)
		Combined TAM-TPB (Taylor & Todd, 1995)
	Extrinsic motivation	Motivational Model MM (Davis et al., 1992)
	Job-fit	Model of PC Utilization MPCU (Thompson et al., 1991)
	Relative advantage	Innovation Diffusion Theory IDT (Rogers, 1962)
	Outcome expectations	Social Cognitive Theory SCT (Bandura, 1986)
Effort Expectancy	Perceived ease of use	Technology Acceptance Model (TAM) (Davis, 1989)
	Complexity	Model of PC Utilization MPCU (Thompson et al., 1991)
Social Influence	Subjective norms	Theory of Reasoned Action TRA (Ajzen & Fishbein, 1980)
		Theory of Planned Behaviour TPB (Ajzen, 1991)
		Technology Acceptance Model (TAM) (Davis, 1989)
		Combined TAM-TPB C-TAM (Taylor & Todd, 1995)
	Social factors	Model of PC Utilization MPCU (Thompson et al., 1991)
	Image	Innovation Diffusion Theory IDT (Rogers, 1962)
Facilitating Conditions	Perceived behavioural control	Theory of Planned Behaviour TPB (Ajzen, 1991)
		Combined TAM-TPB (Taylor & Todd, 1995)
	Facilitating conditions	Model of PC Utilization MPCU (Thompson et al., 1991)
	Complexity	Innovation Diffusion Theory IDT (Rogers, 1962)

2.3. Selected variables for the study

This study engages important variables from the UTAUT2 (Venkatesh et al., 2012) as well as the variable of perceived performance risk (Featherman & Pavlou, 2003) to cope with the extended research model and better understand the factors influencing farmer acceptance of Agriculture 4.0 technologies. Each variable indicates a distinct feature that may influence a farmer's willingness to adopt Agriculture 4.0 technologies. As a result, the variables chosen for this study are presented below.

Firstly, Performance Expectancy (PE) refers to the degree to which individuals believe that using technology will help them achieve gains in job performance (Venkatesh et al., 2012).In the context of Agriculture 4.0, this construct captures farmers' expectations regarding the improvement in crop yield, efficiency, and overall farm productivity due to the adoption of advanced technologies. Previous research has seen this variable for its influence on the adoption of Agriculture 4.0 (Kolady et al., 2021; Paustian & Theuvsen, 2017). Therefore, based on this, the following research hypothesis is proposed:

H1: PE directly and positively influences farmers' intention to adopt Agriculture 4.0 technologies.

Secondly, Effort Expectancy (EE) is defined as the degree of ease associated with the use of the technology (Venkatesh et al., 2012). For farmers, this relates to the perceived ease of learning and using Agriculture 4.0 technologies, including IoT devices, data analytics tools, and automated machinery. Previous research has studied this variable to understand its influence on Agriculture 4.0's adoption (Fragomeli et al., 2024; Giua et al., 2022). Hence, we investigate the research hypothesis that:

H2: EE directly and positively influences farmers' intention to adopt Agriculture 4.0 technologies.

Then, Social Influence (SI) refers to the degree to which individuals perceive that important others believe they should use the new technology (Venkatesh et al., 2012). In agricultural communities, social influence can come from peers, family members, agricultural advisors, and community leaders. In the context of the study, it is the degree to which a farmer believes that important people support their use of Agriculture 4.0 for their daily field tasks. Previous studies have provided empirical support that evidences the impact of SI on the use of a new technology (Moriuchi, 2021). Zhai et al. (2020) and Harisudin et al. (2023) have studied this variable to examine its influence on the adoption of Agriculture 4.0. In this context, our hypothesis is the following:

H3: SI directly and positively influences farmers' intention to adopt Agriculture 4.0 technologies.

Also, Facilitating Conditions (FC) are the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the technology (Venkatesh et al., 2012). This includes access to necessary resources, such as training programs, technical support and funds. Previous research analysed FC from the standpoint of influence on adoption, specifically, Agriculture 4.0 (Da Silveira et al., 2023; Giua et al., 2022). Thus, our research hypothesis is formulated as follows:

H4: FC directly and positively influences farmers' intention to adopt Agriculture 4.0 technologies.

In addition, the Price Value (PV) variable has introduced to capture the farmer's evaluation of whether the benefits of adopting Agriculture 4.0 technologies justify the costs (Venkatesh et al., 2012). Previous studies have evidenced the effect that price/value has on technology adoption, a process that is enhancing in itself, and as such, provides a positive feeling and impact on users (Moorthy et al., 2019; Palau-Saumell et al., 2019). The research hypothesis is formulated as follows:

H5: PV directly and positively influences farmers' intention to adopt Agriculture 4.0 technologies.

Finally, Perceived Performance Risk (PR) refers to the potential negative outcomes associated with the use of technology, such as financial loss and crop failure. This construct, introduced by Featherman and Pavlou (2003), is particularly relevant in the agricultural sector where adopting new technologies often involves significant risks. Understanding PR is crucial as it influences farmers' willingness to adopt innovative agricultural technologies like those encompassed in Agriculture 4.0. Several studies have incorporated PR to predict the adoption of Agriculture 4.0 technologies (Cook et al., 2022; Fragomeli et al., 2024; Kendall et al., 2022). For that, the proposed research hypothesis is the following:

H6: PR directly and negatively influences farmers' intention to adopt Agriculture 4.0 technologies.

The extended UTAUT2 model, with the addition of Perceived Performance Risk, provides a comprehensive framework for understanding the adoption of Agriculture 4.0 technologies. The research model is depicted in Figure 1.

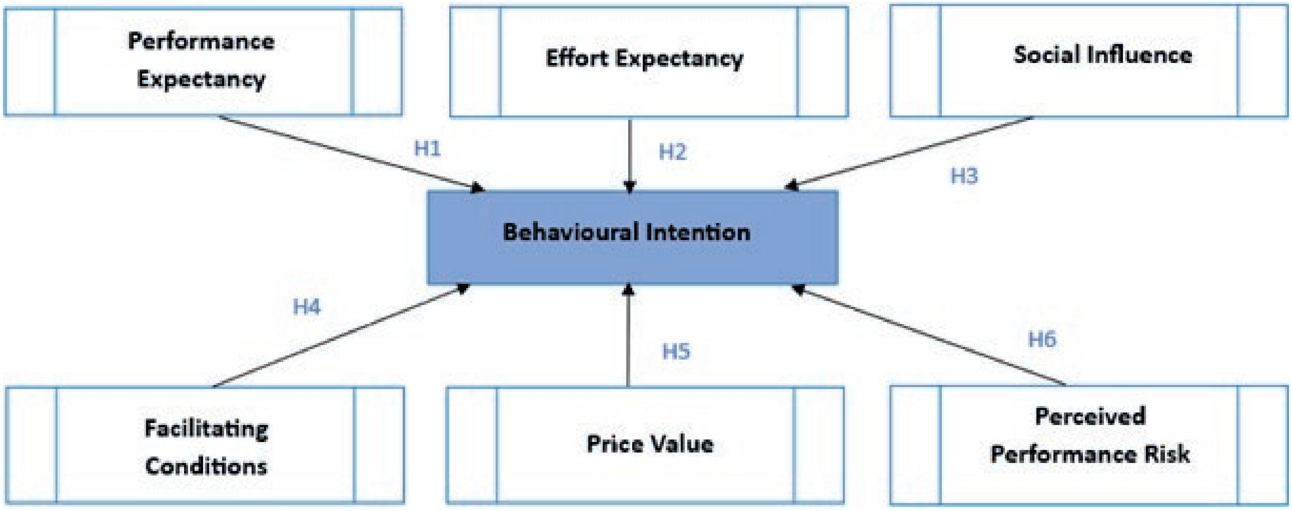

Figure 1. The research model.

3. METHODS

3.1. Survey Design

The survey's questionnaire was divided into three sections. The first section explained the scenario and the research objectives, as well as the definition of Agriculture 4.0, its advantages, and the related investments. To ensure participants clearly understood the concept of Agriculture 4.0, the questionnaire provided a detailed definition inspired by the International Association of Precision Agriculture. Agriculture 4.0 was described as a data-driven farm management strategy where information is collected, processed, and analyzed to guide decisions aimed at improving the efficiency of resource use, productivity, quality, profitability, and sustainability. The definition was accompanied by examples of potential benefits, such as reducing resource waste (e.g., more efficient fertilizer and pesticide use), increasing yields and improving crop quality, enhancing work conditions and efficiency through automation, enabling traceability from production to consumer. Furthermore, examples of specific Agriculture 4.0 tools and their estimated costs were provided. This allowed respondents to better relate to the technologies under investigation and reflect on their potential adoption. A summary is presented in Table 2.

The second section included questions about the farmers' socio-economic characteristics (Table 3). This survey section featured the use of nominal and ordinal scales. The third section contained questions about the major constructs included in the UTAUT2 research model, which are PE, EE, SI, FC, PV, PR , and BI. Specifically, PE was measured using four items. These items were relative to the respondents' belief that Agriculture 4.0 reduces the use of phytosanitary treatments, increases yield, enhances durum wheat's quality, and is compatible with other technologies that the farmer already uses to cultivate durum wheat. EE was evaluated using three items related to respondents' belief that Agriculture 4.0 reduces time and workloads and allows for better organization of work, limiting injuries in the cultivation of durum wheat, especially on the most difficult surfaces. SI was measured using three items reflecting the usefulness of considering the opinion of other farmers regarding the adoption of Agriculture 4.0, the easiness of using Agriculture 4.0 if other farmers close to the respondents' farms utilize it, and the belief of considering the adoption of this technology if farmers' associations will actively promote it. FC was assessed with three items related to the belief of having the necessary knowledge for the adoption of agriculture 4.0 on durum wheat, the belief of having easy access to technical advice in using this technology as well, as the reliance that the stabilization of a specific measure in the Rural Development Program (RDP) in Sardinia Region with a capital contribution greater than or equal to 60% would lead respondents to invest in Agriculture 4.0. Furthermore, the PV construct was assessed with three items related to the belief that Agriculture 4.0 could reduce the cost of durum wheat production, obtaining more profits and promoting the efficient work of the farmers as well. PR was measured with three items regarding the possibility that Agriculture 4.0 could generate more problems than solutions in managing the farm, tying the farmer as well to external consultants and experts, and creating more administrative work diverting the farmer from fieldwork.

Table 2. Precision agriculture tools: functionalities and investment estimates.

Technology / Tool	Functionality	Estimated Cost
4.0 Tractors & Implements	Onboard computer, automatic guidance, automated spraying/fertilization	+ €5,000 over traditional machinery
Weather Stations & DSS (Decision Support)	Real-time weather and field monitoring, pest/disease alerts, irrigation/fertilization advice	From €1,500 upwards
Analytics Platforms & Farm Apps	Integration of field data from sensors, drones, and equipment; decision support	€500–€2,500 per year
Drones	Aerial imaging, multispectral surveys, application of treatments	From €5,000 (excluding pilot license) or €25–€200/ha if outsourced

The intention to invest in Agriculture 4.0 was measured with three items regarding the near future intention of adopting this technology.

Intentions and attitudes cannot be quantified directly (Straub et al., 2004). However, they can be indirectly quantified through observed and measurable indicators using scaling approaches (Gefen et al., 2000). To this end, a five-point Likert-type scale ranging from "strongly disagree" (-2) to "strongly agree" (2) was used to measure the participants' attitudes, beliefs, and opinions about the adoption of Agriculture 4.0 (see Table 4 for the mean and standard deviation of scores). The structural equation model (SEM) was used for the analysis of the results since it allows testing all the relationships between the observed and latent variables simultaneously by combining multiple regression with factor analysis and provides general adjustment statistics (Iacobucci, 2010). In addition, it can consider the measurement error with the observed variables (Hair et al., 2006).

3.2. Data collection

An online questionnaire was distributed from November 20th, 2023 to February 26th, 2024, to 217 randomly selected durum wheat farmers in Sardinia, Italy, with the help of a farmers' association, Coldiretti Sardinia. The sample was obtained using a convenience sampling method facilitated by Coldiretti. It is not statistically representative of the full Sardinian farming population but includes a diverse range of farm sizes and conditions. To better understand the participants' perspectives, we asked whether they believe the land used for cultivating durum wheat meets the criteria for marginal lands. In the questionnaire, we defined marginal lands, according to existing scientific literature (Ahmadzai et al., 2022; Csikós & Tóth, 2023; Food & Nations, 2017; Jussila et al., 2019; Lal, 2004), , as areas characterized by poor soil quality, limited rainfall, extreme temperatures, and inadequate access to transportation and communication networks Respondents who indicated that their land fit this description were classified as cultivating in marginal conditions, while those who did not were classified as operating in non-marginal conditions. By that, the sample was divided into two groups: farmers located in marginal areas and those in non-marginal areas. Overall, 86 questionnaires were eliminated due to incomplete ones and small duration completion (less than 4 minutes, i.e., less than half the median duration of the interview).

In Table 3, we present the demographic and socioeconomic characteristics of the participants in marginal and non-marginal conditions. The majority of respondents are male in both non-marginal and marginal conditions, with a slightly higher percentage of females in marginal conditions. The age distribution is quite similar between the two groups, with the majority being between 50-64 years old. This indicates that middle-aged farmers form the core demographic in both non-marginal and marginal conditions. Education levels are comparable across both conditions, with most respondents having a high school diploma or less. Most farms are multi-generational family farms, with a slightly higher presence of first-generation farms in marginal conditions (a first-generation farm refers to one where the current farmer is the first in their family to establish or manage a farming business, as opposed to multi-generational family farms passed down through successive generations). There is a notable difference in the likelihood of having a successor between the two conditions. Non-marginal farms are more optimistic about having successors compared to marginal farms, where a significant percentage are unlikely to have successors. This is aligned with Lobley et al. (2010) who showed that farm succession planning is more prevalent in financially stable farms, where future prospects are more secure and with Kimhi and Nachlieli (2001) who indicated that farm profitability and stability significantly influence the likelihood of having successors, with marginal farms often facing more uncertainty. Moreover, yield levels are

Table 3 Demographic and socio-economic characteristics of the respondents.

Socio-Economic Variables	Category	Non-Marginal Conditions (N=72)		Marginal Conditions (N=59)	
		Frequency	%	Frequency	%
Gender	Male	63	87.50	49	83.05
	Female	9	12.50	10	16.95
Age	18-49 years	24	33.33	19	32.20
	50-64 years	37	51.39	30	50.85
	> 65 years	11	15.28	10	16.95
Educational level	Lower than high school diploma	35	48.61	28	47.46
	High school diploma	31	43.06	24	40.68
	University degree	6	8.33	7	11.86
Characteristics of the farm	Family farm for several generations	62	86.11	49	83.05
	First generation family farm	9	12.50	10	16.95
	Part of a corporate enterprise	1	1.39	0	0
The probability that the farm will have a successor	None	8	11.11	6	10.17
	Unlikely	11	15.28	26	44.08
	Likely	40	55.56	21	35.59
	Very Likely	5	6.94	3	5.08
	Certainly	8	11.11	3	5.08
Average yield per hectare of the area cultivated with durum wheat	< 2 t/ha	5	6.94	8	13.56
	2.1 - 3 t/ha	39	54.17	37	62.72
	3.1 - 4 t/ha	23	31.95	13	22.03
	> 4.1 t/ha	5	6.94	1	1.69
Experience Agriculture 4.0 techniques	I have no experience with Agriculture 4.0 techniques.	32	44.44	33	55.94
	I don't use these techniques, but I've seen them used by others and I think I'm somewhat familiar with them.	13	18.06	13	22.03
	I use Agriculture 4.0 techniques.	27	37.50	13	22.03

higher in non-marginal conditions, with a notable percentage achieving between 2,1-4 tons/ha. Marginal conditions show a greater proportion of farms with yields less than 2 tons/ha. This could be due to the fact that yield performance is related to farm management practices and resource availability, which are typically better in non-marginal conditions (Fischer et al., 2014) and as well the fact that non-marginal lands benefit from better soil quality, access to water, and inputs leading to higher yields compared to marginal lands (Tilman et al., 2011).

To explore group differences, pairwise t-tests were performed to assess differences between marginal and non-marginal conditions. To save space, we do not report these t-tests. However, all the pairwise t-tests were significant at the 5% level of confidence. Thus, the constructs showed significant differences between the two areas. The analysis of Agriculture 4.0-related items (Table 4) reveals notable differences in perceptions between non-marginal and marginal farmers. Each construct was calculated by taking the average of all related items. Non-marginal farmers consistently report higher scores across all UTAUT2 constructs compared to marginal farmers. They perceive Agriculture 4.0 as more beneficial (higher PE and PV), easier to use, and better supported socially and institutionally. In contrast, marginal farmers show greater PR and lower BI to adopt these technologies.

3.3. Modelling analysis framework

Due to the limited data available, we had to create a unified model to offer a comprehensive understanding of the factors influencing the adoption intentions of Agriculture 4.0 technology. Consequently, we merged data from both marginal and non-marginal areas to develop a consolidated model that reflects the overall regional dynamics.

A confirmatory factor analysis (CFA) was carried out using IBM SPSS AMOS version 26 to evaluate the measurement model's validity, focusing on convergent validity, discriminant validity, and internal consistency of the constructs.

Table 4. Summary statistics of the Agriculture 4.0 related items and latent components.

Agriculture 4.0 items and latent components	Variables	Non-Marginal Conditions (N=72)		Marginal Conditions (N=59)	
		Mean(M)	StDev(SD)	Mean(M)	StDev(SD)
Performance Expectancy (I Believe that…)	*PE*	*0.93*	*0.07*	*0.68*	*0.09*
Agriculture 4.0 would help the cultivation of durum wheat by reducing the use of resources such as, for example, fertilizers and phytosanitary treatments.	PE1	1.15	0.09	0.80	0.12
Thanks to Agriculture 4.0, we can increase the yield per hectare of durum wheat.	PE2	0.92	0.09	0.54	0.12
Agriculture 4.0 allows for a better quality of durum wheat production.	PE3	0.85	0.09	0.49	0.13
Agriculture 4.0 is compatible with the other technologies I already use to cultivate durum wheat.	PE4	0.88	0.09	0.81	0.11
Effort Expectancy (I Believe that …)	*EE*	*0.76*	*0.07*	*0.58*	*0.10*
Agriculture 4.0 allows us to reduce time and workload in the cultivation of durum wheat.	EE1	0.89	0.10	0.66	0.13
Agriculture 4.0 allows for better organization of work in cultivating durum wheat.	EE2	0.97	0.08	0.81	0.10
Agriculture 4.0 can limit injuries in the cultivation of durum wheat, especially on the most difficult surfaces.	EE3	0.46	0.10	0.22	0.14
Social Influence (I Believe…)	*SI*	*0.83*	*0.06*	*0.60*	*0.11*
It is useful to consider the opinions of other farmers regarding the adoption of Agriculture 4.0 techniques.	SI1	0.92	0.08	0.81	0.13
It would be easier to use Agriculture 4.0 techniques if other farmers close to my farm also used it.	SI2	0.69	0.09	0.41	0.13
I would consider adopting Agriculture 4.0 techniques if Farmers' Associations actively promoted their use.	SI3	0.88	0.08	0.58	0.14
Facilitating Conditions (I Believe …)	*FC*	*0.76*	*0.07*	*0.51*	*0.11*
I have all the necessary knowledge for the adoption of Agriculture 4.0 in the cultivation of durum wheat.	FC1	0.26	0.12	-0.03	0.17
The stabilization of a specific measure in the RDP in the Sardinia Region, with a capital contribution greater than or equal to 60% for companies that invest in Agriculture 4.0, would lead me to invest in these new technologies.	FC2	1.15	0.09	0.83	0.16
Agriculture 4.0 technologies are compatible with those I already use.	FC3	0.72	0.10	0.54	0.14
Price Value (Thanks to the use of Agriculture 4.0 …)	*PV*	*0.87*	*0.08*	*0.75*	*0.13*
A reduction in the cost of durum wheat production can be achieved.	PV1	0.89	0.09	0.71	0.15
I could work more efficiently.	PV2	0.96	0.08	0.88	0.13
I could obtain a greater profit.	PV3	0.75	0.09	0.66	0.14
Perceived Performance Risk (I believe it is likely that the use of Agriculture 4.0 techniques will …)	*PR*	*0.00*	*0.10*	*0.14*	*0.12*
Generate more problems than solutions in managing my farm.	PR1	- 0.24	0.12	-0.34	0.16
Tie me to external consultants and experts due to the level of sophistication in applying these techniques.	PR2	0.25	0.12	0.46	0.15
Create more administrative work, diverting my business from fieldwork.	PR3	0.00	0.12	0.29	0.15
Behavioural Intention	*BI*	*0.38*	*0.11*	*-0.12*	*0.14*
I will introduce Agriculture 4.0 to durum wheat cultivation in the coming months.	BI1	0.35	0.11	-0.15	0.16
In the near future, I plan to use Agriculture 4.0 techniques in growing durum wheat.	BI2	0.58	0.11	0.27	0.16
I have already planned to use Agriculture 4.0 techniques on my farm.	BI3	0.22	0.12	-0.49	0.16

Convergent validity was assessed by examining the reliability of measurement items (factor loadings), the composite reliability (CR) of each construct, and the average variance extracted (AVE) (Anderson & Gerbing, 1988). Standardized factor loadings ranged from 0.58 to 0.96, all exceeding the recommended minimum of 0.50 (Gefen et al., 2000). The composite reliability values were consistently above the threshold of 0.70, indicating strong internal consistency of the latent constructs (Heinzl et al., 2011). Additionally, the AVE values, which measure the proportion of variance explained by the latent variables relative to measurement error, ranged between 0.50 and 0.70, exceeding the minimum acceptable value of 0.50 (Fornell & Larcker, 1981). These results, detailed in Table 5, demonstrate high reliability and good convergent validity of the constructs, as they are well-correlated with each other within the model.

Discriminant validity was evaluated using the Heterotrait-Monotrait ratio (HTMT) (Henseler et al., 2015) with coefficients needing to be below 0.90 to confirm that the latent variables are distinct. The results, shown in Table 6, indicated that all HTMT values were below 0.90, confirming that the constructs are appropriately differentiated.

The overall fit of the measurement model was assessed through three key goodness-of-fit indices: the chi-square to degrees of freedom ratio (PCMIN/DF), the Comparative Fit Index (CFI), and the Standardized Root Mean Square Residual (SRMR). According to established criteria, the model is considered to fit well if the PCMIN/DF ratio is less than 3, the CFI exceeds 0.90, and the SRMR is below 0.08 (Hair et al., 2006). The results showed PCMIN/DF = 2.330, CFI = 0.921, and SRMR = 0.080, indicating that the measurement model demonstrates a good fit for the data.

Table 5. Results for the measurement model.

Constructs	Items	Loading Values	Cα	CR	AVE
Performance Expectancy	PE1	0.74	0.86	0.87	0.53
	PE2	0.85			
	PE3	0.91			
	PE4	0.58			
Effort Expectancy	EE1	0.83	0.79	0.78	0.50
	EE2	0.80			
	EE3	0.62			
Social Influence	SI1	0.58	0.72	0.75	0.50
	SI2	0.63			
	SI3	0.91			
Facilitating Conditions	FC1	0.60	0.70	0.69	0.50
	FC2	0.84			
	FC3	0.58			
Price Value	PV1	0.77	0.87	0.87	0.69
	PV2	0.86			
	PV3	0.86			
Perceived Performance Risk	PR1	0.60	0.74	0.75	0.50
	PR2	0.71			
	PR3	0.81			
Behavioural Intention	BI1	0.83	0.89	0.87	0.70
	BI2	0.96			
	BI3	0.88			

Table 6. Heterotrait-monotrait ratio (HTMT) results.

	BI	EE	FC	PE	PR	PV	SI
BI							
EE	0.523						
FC	0.834	0.621					
PE	0.632	0.758	0.676				
PR	0.422	0.178	0.357	0.315			
PV	0.684	0.692	0.769	0.647	0.267		
SI	0.579	0.513	0.750	0.554	0.184	0.564	

3.4. Structural model assessment

3.4.1. Dataset sample validation

With the aim of validating the adequacy of samples collected, Hoelter's N critical index was applied with a significance level of 0.05, equivalent to 95% confidence (Bollen & Liang, 1988; Hoelter, 1983). The size of the sample is131 questionnaires and the Hoelter's N (0.05) is 83 which exceeds the commonly cited minimum threshold of 75, indicating an acceptable sample size for model fit (Garson, 2015).

3.4.2. Framework model analysis

After performing the overall goodness of fit of the research model indicating a good fit to the data (chi-square to degrees of freedom ratio (PCMIN/DF) of 2.330, Comparative Fit Index (CFI) of 0.921, Standardized Root Mean Square Residual (SRMR) of 0.080), the next step in the analysis involves assessing the explanatory power of the model's dependent variable, measured as R^2, which reflects how well the independent variables account for variations in the dependent variable. In this study, the R^2 for behavioural intention was found to be 0.49, meaning that 49% of the variability in behavioural intention is explained by the independent variables in the model (Kapoor & Singh, 2023; Schukat & Heise, 2021). The f^2 values (the change in R^2 when an exogenous variable is removed from the model) range from 0.09 to 0.16, suggesting a small to medium effect size (Cohen, 2013) as indicated in Table 7. Further analysis involves examining the structural relationships among constructs using the Structural Equation Modelling (SEM) approach with the IBM SPSS AMOS version 26 software. The results of the path coefficient analysis are shown and detailed in Figure 2 and Table 8. Findings reveal that FC significantly affects behavioural intention (β=0.625, p-value=0.010), while PR negatively impacts behavioural intention (β=-0.315,

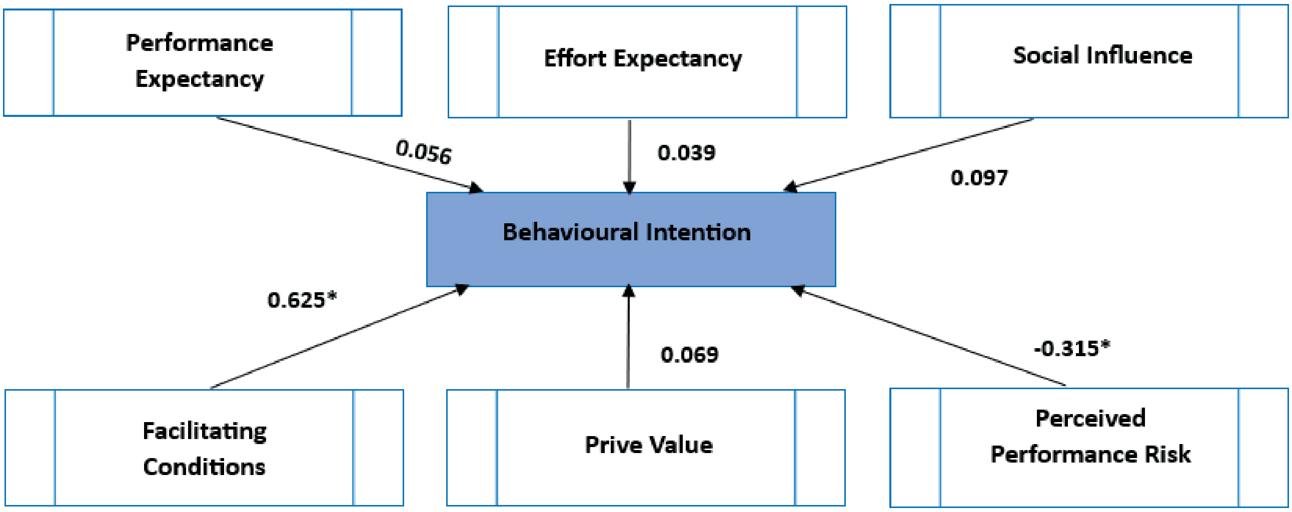

Figure 2. Final structural model.

p-value=0.010). This suggests that participants who perceive higher performance risks are less likely to invest in Agriculture 4.0 technologies. The analysis highlights that FC exerts the most substantial influence on the intention to adopt these technologies. Conversely, the hypotheses related to PE (β=0.056, p-value=0.729), EE (β=0.039, p-value=0.792), SI (β=0.097, p-value=0.686), and PV (β=0.069, p-value=0.685) were not supported, indicating that these factors do not significantly affect farmers' intentions to adopt Agriculture 4.0 technologies for durum wheat cultivation. It's worth noting that demographic variables such as age, education, and previous experience were initially considered for inclusion in the model. However, upon analysis, none of them were statistically significant, and their inclusion resulted in a decrease in the model's goodness of fit. Therefore, to maintain the model's validity and optimal fit, demographic variables were excluded from the analysis.

Table 7. F-square results.

Constructs	F-square
PE → BI	0.09
EE → BI	0.13
SI → BI	0.09
FC → BI	0.16
PV → BI	0.11
PR → BI	0.10

Table 8. Results.

Hypothesis	B	p-value	Decision
H1: PE→ BI	0.056	0.729	Unsupported
H2: EE → BI	0.039	0.792	Unsupported
H3: SI → BI	0.097	0.686	Unsupported
H4: FC → BI	0.625*	0.010	Supported
H5: PV →BI	0.069	0.685	Unsupported
H6: PR →BI	-0.315*	0.010	Supported

Note: *p-value < 0.05.

4. DISCUSSION AND POLICY RECOMMENDATIONS

4.1. Differences in impact between marginal and non-marginal areas and their policy implications

As emerged from Table 4, non-marginal farmers demonstrated higher performance expectancy, effort expectancy, social influence, facilitating conditions, and price value compared to marginal farmers. In this context, non-marginal farmers perceived Agriculture 4.0 technologies as beneficial for resource efficiency, yield improvement, reduced effort, and work efficiency.

Policies and interventions for farmers should aim to reinforce their positive behavioural intentions and help them scale adoption. Information provision (Hines et al., 1987; Stern & Dietz, 2002) can focus on showing case studies of successful implementation from peer farmers, inducing a reduction in resource use, increased yield, and efficient work, accompanied by less effort. These campaigns could also be amplified to present, in the form of infographics or videos, how Agriculture 4.0 can contribute to sustainability goals by adopting it. Additionally, incentives (van Valkengoed et al., 2022) such as stabilizing a specific measure within the regional RDP can reward those who adopt these practices. Commitment strategies (Cialdini, 2009) can motivate farmers to adopt new technologies because people are driven to remain consistent with their actions and beliefs, leading them to feel obligated to fulfil their promises. Public commitments are made to try specific technologies, and these pledges can be recognized in public forums through certifications or awards. Public recognition inspires individuals and sets positive examples in farming communities, encouraging others to follow suit (Cialdini, 2009; Schultz et al., 2007).

In contrast, marginal farmers expressed hesitancy and a negative behavioural intention due to higher perceived performance risks related to their concerns about being linked to external consultants and lower availability of facilitating conditions, especially for technology knowledge and limited access to financial resources. To increase knowledge and build technological trust, workshops, and training programs can help marginal farmers understand how to efficiently utilize Agriculture 4.0 technologies and understand their benefits (Kutter et al., 2011; Menozzi et al., 2015). Implementing pilot programs could enable marginal farmers to test these technologies on their farms for a limited time without long-term commitments.

Additionally, the government should prioritize providing subsidies or establishing low-interest loans to facilitate access to Agriculture 4.0 technologies. These technologies can lead to more efficient resource use and reduced environmental impact; outcomes that benefit not only farmers but also the broader public through environmental protection, rural development, and climate change mitigation. Insurance incentive strategies can help reduce obstacles and ease fears of financial instability by offsetting potential losses during the transition to new technologies (Mills, 2007; Wreford et al., 2017). Policymakers can support marginal farmers by collaborating with local institutions and experts to define small, attainable goals that gradually build trust and familiarity with technology. According to Appelbaum and Hare (1996), setting clear and realistic objectives – whether individually or through collective initiatives – can strengthen farmers' self-efficacy and motivation, ultimately supporting more ambitious technological transitions.

4.2. The Unified UTAUT2 model

Results of the unified UTAUT2 model supported H4 and H6 hypotheses as seen in Table 6, showing that facilitating conditions and perceived performance risk significantly influence farmers' intention to adopt Agriculture 4.0 technologies on durum wheat within our convenience sample. The results showed that facilitating conditions significantly impacted farmers' intentions to use Agriculture 4.0 technologies. Our findings align with Fragomeli et al. (2024), who emphasize that practical and financial support from government initiatives significantly influences the adoption of Agriculture 4.0. This support often includes subsidies, training and educational programs, and technical assistance, which help farmers overcome barriers to adopting new technologies. For instance, government-funded training sessions can provide information to improve farmers' understanding of how to use Agriculture 4.0 technologies based on IoT devices and data analytics platforms, making it easier for them to integrate these technologies into their operations. As well, creating educational programs explaining the challenges in traditional farming practices and the environmental and economic benefits of Agriculture 4.0 can also positively induce the adoption of Agriculture 4.0. Araújo et al. (2021) highlight that having access to essential technological infrastructure such as IoT sensors and data analytics tools is critical for successful implementation. When farmers have the necessary resources, infrastructure, and knowledge, they are more likely to adopt and utilize Agriculture 4.0 technologies effectively.

Perceived performance risk had a negative and significant impact on the intention to adopt Agriculture 4.0 technologies. Perceived performance risk encompasses concerns about the reliability and effectiveness of new technologies. Benos et al. (2022) found that if farmers are uncertain about whether Agriculture 4.0 will deliver the promised benefits or if they fear potential operational failures or being linked to external consultants, they may be hesitant to adopt these technologies. This concern can stem from previous experiences with technology failures or from insufficient evidence demonstrating the technology's effectiveness. Abikari (2024) further supports this by showing that perceived risks, including those related to technology performance, are crucial in adoption decisions. Duong et al. (2019) also highlight that uncertainties about new technologies' effectiveness can significantly impact farmers' willingness to adopt them. To mitigate these concerns and build trust, not only clear demonstrations, pilot projects, and empirical evidence of technology benefits should be emphasized but also providing financial incentives, such as subsidies for purchasing Agriculture 4.0 technologies or microloans (Fragomeli et al., 2024; Osorio et al., 2024). It is important to note that financial incentives and public subsidies may strongly influence farmers' awareness and perceived value of Agriculture 4.0 technologies. Menozzi et al. (2015) indicates that many Italian farmers are primarily driven by economic benefits. This pattern could affect how farmers evaluate the usefulness and feasibility of adopting such technologies, especially if some options are more frequently promoted through subsidy programs or public campaigns. Additionally, media coverage and institutional promotions often emphasize the availability of tax credits or financial contributions for specific Agriculture 4.0 technologies (Confagricoltura, 2024; ESG360, 2023), which may shape farmer awareness and preferences toward subsidized solutions.

Contrary to expectations, performance expectancy did not significantly influence the intention to use Agriculture 4.0 technologies. Although performance expectancy scores were relatively positive in both marginal (0.68) and non-marginal areas (0.96), this construct did not significantly influence behavioural intention in our model. This finding contrasts with Im et al. (2008) and Araújo et al. (2021), who found that when farmers perceive significant improvements in their operations due to new technologies, they are more inclined to adopt them. A possible explanation for our results could be that, while farmers acknowledge the potential benefits of Agriculture 4.0, these benefits alone are not sufficient to drive adoption. This may be due to overriding concerns such as performance risk, limited infrastructure and experience with digital tools, which may weaken the link between perceived performance and the intention to adopt, especially in marginal areas. Another possible explanation for our result could be that the perceived benefits of Agriculture 4.0 technologies might not align with the specific needs of farmers in Sardinia. If farmers do not clearly see how these technologies will enhance their productivity or efficiency, their intention to adopt may not be strongly influenced by performance expectancy (Kutter et al., 2011; Menozzi et al., 2015).

Effort expectancy also did not impact on the intention to adopt Agriculture 4.0 technologies. This result differs from findings by Fragomeli et al. (2024) and Abikari (2024), who suggested that technologies perceived as user-friendly and requiring minimal additional effort are more likely to be adopted. Our findings are consistent with Araújo et al. (2021), which noted that difficulties in integrating Agriculture 4.0 technologies with existing systems can act as barriers to adoption. If the technologies are perceived as challenging to integrate, farmers may be discouraged from using them despite their potential benefits. This suggests that high expectancy, or the perception of increased effort and complexity, could negatively impact adoption intentions.

Social influence did not significantly affect the intention to adopt Agriculture 4.0 technologies. This finding is consistent with Li et al. (2024) which found that societal norms and peer pressure do not always positively impact the intention to use Agriculture 4.0 technologies. Farmers may resist adopting new technologies due to scepticism from their community or a preference for traditional methods. Yap and Al-Mutairi (2024) also highlight that negative social perceptions within certain farming communities can hinder technology acceptance. If the broader community holds negative views about Agriculture 4.0 technologies, individual farmers may be less inclined to adopt them, even if they recognize potential benefits.

Price value did not significantly influence the intention to adopt Agriculture 4.0 technologies such as 4.0 tractors, weather stations and DSS, analytics platforms, farm applications and drones. This result contrasts with findings by Araújo et al. (2021) and Fragomeli et al. (2024) who highlighted that farmers often justify the initial investment in Agriculture 4.0 technologies through anticipated long-term economic returns, such as increased crop yields and improved resource management. The lack of significant impact in our study might suggest that other factors, such as perceived risks or the complexity of technology, overshadow price considerations in the adoption decision-making process.

Overall, the extended UTAUT2 framework provides a solid foundation for understanding how facilitating conditions and perceived performance risk influence Sardinian wheat farmers' intentions to adopt Agriculture 4.0 technologies. Designing a supportive choice architecture (Thaler & Sunstein, 2008) can simplify the adoption process. Ensuring easy access to Agriculture 4.0 technologies can reduce difficulties. This comprehensive approach, combining education, financial support, social recognition, and accessibility, addresses the barriers to adoption while enhancing farmers' readiness to embrace Agriculture 4.0 technologies.

5. CONCLUSIONS

The study highlighted notable differences in adoption intentions between marginal and non-marginal farmers of durum wheat in Sardinia, driven by disparities in facilitating conditions, perceived benefits, and social influence. Non-marginal farmers demonstrated greater readiness and positive intentions toward Agriculture 4.0 technologies, while marginal farmers faced barriers such as limited resources and higher perceived risks although they had positive performance expectancy, effort expectancy, social influence, facilitating conditions and price value. Combining data from both groups provided a holistic understanding of regional adoption dynamics showing that facilitating conditions and perceived performance risk significantly affect the intention to adopt Agriculture 4.0 technologies. Facilitating conditions were found to have a positive and substantial impact, highlighting the critical role of support mechanisms such as financial aid, technical training, and access to technological infrastructure in promoting the adoption of these advanced technologies. In contrast, perceived performance risk negatively influenced adoption intentions, reflecting farmers' concerns about the reliability and effectiveness of new technologies.

Several targeted interventions are recommended to enhance the adoption of Agriculture 4.0 technologies. It is essential to focus on providing easy access to technical advice and educational programs through regional extension services. This approach will enable farmers to effectively utilize Agriculture 4.0 technologies and reduce barriers to adoption. Establishing accessible platforms for technical support will ensure that farmers are well informed about the benefits and functionalities of these technologies.

Furthermore, improving the educational qualifications of technicians working in regional extension services is necessary to address the knowledge gap related to Agriculture 4.0 technologies. This aligns with the findings of Caffaro and Cavallo (2019) that lower levels of education were linked to higher perceptions of economic barriers, which in turn were negatively correlated with the adoption of smart farming technologies. Universities and educational institutions should develop specialized courses or master's programs focused on these technologies to equip technicians with the skills and knowledge required to support farmers and facilitate successful implementation.

Overall, by concentrating on enhancing facilitating conditions and addressing perceived performance risks, stakeholders can create a more supportive environment for the adoption of Agriculture 4.0 technologies. These interventions will help overcome existing barriers, promote the integration of innovative solutions in durum wheat farming, and ultimately improve productivity and sustainability within the agricultural sector.

6. LIMITATIONS

While this study provides valuable insights into adopting Agriculture 4.0 technologies in durum wheat farming, it is important to acknowledge several limitations. The study is constrained by its geographical focus on Sardinia, which may limit the generalizability of the findings to other regions with different agricultural contexts or technological infrastructures. Additionally, using a convenience sampling method further limits the representativeness of the findings. Therefore, the results can be generalised to the wider farming population in Sardinia. Additionally, the study relies on self-reported data from farmers, which may introduce biases related to respondents' perceptions or reporting accuracy. The adoption intentions assessed are also based on subjective assessments, which might not fully capture actual technology usage or long-term adoption outcomes. Furthermore, the research does not account for all possible variables influencing technology adoption, such as economic fluctuations or policy changes, which could impact the relevance of the findings over time. As highlighted by Menozzi et al. (2015), economic incentives often outweigh environmental concerns in Italian agricultural decision-making. Therefore, farmers may have expressed more favourable opinions toward technologies with known funding opportunities, possibly biasing the intention data. Future studies could attempt to control for this effect by comparing knowledge of subsidized vs non-subsidized solutions. Also, future research could benefit from a broader geographical scope, longitudinal studies, and a more comprehensive analysis of external factors to enhance the understanding of Agriculture 4.0 adoption across diverse agricultural settings.

DISCLAIMER

The data supporting this study's findings are available as a supplementary file to this paper.

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Enabling technologies in citrus farming: A living lab approach to agroecology and sustainable water resource management

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Abstract. This study examines the role of enabling technologies in the agroecological transition, focusing on sustainable water management in citrus farming through the participatory approach of a Living Lab in the Inner Area of Calatino in Sicily. The analysis is based on a comparison of two citrus farms: one equipped with advanced digital tools (sensors, decision support systems, and real-time monitoring), and one with a traditional management approach. Through the joint application of economic analysis, Monte Carlo simulation and sensitivity analysis, it was possible to estimate the effects of technology adoption. Findings reveal that enabling technologies reduce water consumption by 33%, increase yield per hectare by 16%, and boost net profit by 25% (+€2,780/ha), enhancing resource efficiency and lowering operational costs. Additionally, the Living Lab facilitated knowledge transfer, fostered collaboration, and mitigated resistance to innovation, highlighting the need for targeted training and institutional support to promote broader adoption. These results provide valuable insights for policymakers and stakeholders, demonstrating how digital solutions can drive sustainability, economic viability, and resilience in agriculture, but also for farmers, providing operational tools to improve farm efficiency and profitability.

Keywords: agroecology, enabling technologies, living lab, water management, citrus farming.

1. INTRODUCTION

In recent decades, agroecology has become a key strategy to tackle sustainability challenges in agriculture. It combines ecological, economic, and social principles to address problems like soil degradation, biodiversity loss, climate change, and economic inequality This paradigm not only protects the environment but also offers economic advantages by fostering local markets, short supply chains, and more equitable and resilient food systems (Van der Ploeg et al., 2019; D'Annolfo et al., 2017; Poux and Aubert, 2018).

Agroecology successfully integrates environmental sustainability with agricultural productivity through practices that enhance soil fertility, promote crop diversification, and reduce reliance on chemical inputs. Studies have demonstrated that agroecological systems can achieve yields comparable to those of conventional agriculture while delivering significant benefits in terms of lower environmental impact and increased resilience to climate change (D'Annolfo et al., 2017; Poux and Aubert, 2018). Moreover, adopting agroecological practices improves the quality of food produced, contributing to human health and the wellbeing of farming communities (Belliggiano and Conti, 2019).

Other studies have highlighted how agroecological systems can generate economic benefits for farmers by reducing dependence on external inputs and increasing long-term profitability (Van der Ploeg et al., 2019; D'Annolfo et al., 2017). However, the agroecological transition requires adequate support from public policies, including instruments that promote the adoption of agroecological practices and facilitate market access for small-scale producers (Gava et al., 2022; Schiller et al., 2020). Agroecology not only promotes more sustainable and resilient farming practices but also represents a comprehensive approach to agri-food governance, fostering farmers' autonomy, food sovereignty, and social justice (Van der Ploeg et al., 2019).

A key factor in accelerating the agroecological transition is the integration of Key Enabling Technologies (KETs), such as digital tools, Internet of Things (IoT) sensors, artificial intelligence, and precision agriculture systems, which optimize resource management and reduce waste (Chollet et al., 2023; Bellon-Maurel et al., 2022). These technologies provide real-time data on soil and crop status, boosting efficiency and reducing environmental impact (Fischetti et al., 2025; Ewert et al., 2023). By adapting practices to local conditions, KETs offer agroecology a practical path to greater sustainability (Ewert et al., 2023).

However, the integration of KETs into agroecology has sparked debate within the agroecological community, dividing the sector into two opposing perspectives. Traditionalists argue that agroecology should preserve traditional practices and local knowledge, avoiding reliance on technological tools that could disrupt the ecological and social balance of agricultural systems. Modernizers see innovation as an opportunity to improve sustainability and efficiency. They support the responsible integration of new technologies to make farming models more resilient (Bertoglio et al., 2021; Menozzi et al., 2015; Arata and Menozzi, 2023).

Despite these concerns, the synergy between agroecology and enabling technologies offers significant potential for sustainable development, particularly in inner areas. These territories can benefit from agroecological innovation to revitalize agricultural activity and enhance local natural resources (Gava et al., 2025; Verharen et al., 2021). Moreover, inner areas offer unique opportunities for agroecological innovation due to the presence of traditional farming systems and the availability of high-quality natural resources (Verharen et al., 2021). The integration of modern technologies into agroecological production systems – through decision-support tools, knowledge-sharing platforms, and mobile applications for farm management (Espelt et al., 2019; Emeana, 2021) – represents a concrete opportunity to facilitate the transition to more sustainable models. These tools can help reduce barriers to the adoption of agroecological practices and strengthen producers' competitiveness in the market (Maurel and Huyghe, 2017).

In this context, Living Labs emerge as essential tools for promoting an integrated system that combines technology and agroecology. These participatory innovation spaces engage farmers, researchers, policymakers, and other agri-food system stakeholders, fostering the experimentation of innovative solutions and facilitating knowledge transfer at the local level (Larbaigt et al., 2024; Berghez et al., 2019; Giampietri et al., 2020; Ouattara et al., 2024). Living Labs serve as a bridge between scientific research and agricultural practice, allowing technologies to be tailored to specific territorial needs, thereby improving farmers' acceptance of new practices and enhancing the effectiveness of transition strategies (Giagnocavo et al., 2022; Belliggiano and Conti, 2019).

A concrete example of such integration is the experimental initiative focused on citrus farming in the inner area known as the "Calatino," aimed at demonstrating its economic feasibility. This territory encompasses nine municipalities in central-eastern Sicily (Caltagirone, Grammichele, Licodia Eubea, Mazzarrone, Mineo, Mirabella Imbaccari, San Cono, San Michele di Ganzaria, and Vizzini) all within the Metropolitan City of Catania. The area represents 1.6% of the regional population and spans approximately one thousand square kilometres.

In this Living Lab a range of integrated systems have been installed, incorporating weather stations, sensors, and decision-support systems, with the aim of optimising water usage. This initiative is expected to enhance resource use efficiency, while concurrently improving the resilience and economic viability of the production system (Fischetti et al., 2025; Ewert et al., 2023; Rocchi et al., 2024).

Citrus farming was selected for this study because it represents one of the most relevant agricultural sectors in Sicily, with more than 30% of national citrus production, and oranges covering more than 60% of the total supply (Scuderi et al., 2022). While remaining a leading global player, Italy has lost leadership in the last decade due to structural criticalities in strategic areas such as

Sicily (Rapisarda et al., 2015), which nevertheless maintains 55 % of the national area dedicated to citrus (about 61 000 ha) (Istat, 2022).

The research was based on the hypothesis that adopting an integrated system (weather station, sensors, and decision-support system) enables a more sustainable management of water resources, reducing waste (water consumption) and environmental costs while positively impacting operational costs, revenues, and farm economic efficiency.

Therefore, the following research questions were formulated:

Q1. How can the integration of enabling technologies accelerate the agroecological transition in inner areas?
Q2. What are farmers' perceptions and resistances regarding the adoption of digital tools and precision agriculture systems in the agroecological context?
Q3. What economic and environmental impacts result from combining agroecological practices with innovative technologies, particularly in the citrus sector?
Q4. To what extent do Living Labs facilitate the creation of an integrated system that merges technology and agroecology, fostering sustainability in inner areas?

2. MATERIALS AND METHODS

2.1. Study Area

The Inner Area of Calatino covers approximately 982 km² and includes nine municipalities in the province of Catania: Caltagirone, Grammichele, Licodia Eubea, Mazzarrone, Mineo, Mirabella Imbaccari, San Cono, San Michele di Ganzaria, and Vizzini. The area has a population of approximately 70,606 inhabitants. It is characterized by an economy strongly linked to agriculture, with a significant presence of farms and specialized crops, as well as artisanal activities primarily related to ceramics and small-scale industry.

The utilized agricultural area (UAA) of the Inner Area of Calatino amounts to 56,330 hectares, of which approximately 4% is allocated to organic farming. Organic production is particularly concentrated in the municipalities of San Cono (11%) and Vizzini (9.9%). Overall, the Calatino region hosts 279 organic farms, primarily cultivating citrus fruits, vineyards, olive groves, and herbaceous crops, representing a growing sector.

One of the most representative sectors in terms of income and employment in Calatino is citrus production, particularly concentrated in the municipality of Mineo, which hosts vast plantations dedicated to the cultivation of oranges and mandarins (Table 1).

Additionally, other municipalities in the area, such as Caltagirone and Vizzini, also feature extensive citrus orchards, although integrated with other agricultural productions. Mazzarrone is renowned for its PGI table grapes, while San Cono stands out for its PDO prickly pear (Figure 1).

Local agriculture is characterized by a combination of herbaceous crops (cereals, legumes, forages) and tree crops (vineyards, olive groves, citrus orchards, and fruit trees), with a huge portion of the area dedicated to organic or transitioning farming methods.

The University of Catania has launched a Living Lab with the aim of fostering the transition towards sustainability and a circular economy. The initiative involves farmers, local institutions, environmental organisations and consumers, and is focused on establishing the Calatino Bio-district. Among the various crops present,

Table 1. Agricultural land and crops in the Calatino region.

Municipality	Area (km²)	Farms	Utilised agricultural area (ha)	Citrus groves (ha)	Vineyards (ha)	Olive groves (ha)	Herbaceous crops (ha)
Caltagirone	383.37	2,368	20,437	615	892	1,469	10,659
Grammichele	32.07	511	1,698	480	21	176	665
Licodia Eubea	112.45	823	6,132	68	956	342	2,660
Mazzarrone	34.78	352	1,905	17	865	160	375
Mineo	245.27	1,859	15,423	3,000	30	952	5,573
Mirabella Imbaccari	15.3	214	990	4	9	117	419
San Cono	6.63	100	278	1	4	33	58
San Michele di Ganzaria	25.81	217	904	4	45	139	535
Vizzini	126.75	463	8,563	170	48	296	4,080
Total Calatino	982	6,907	56,330	4,359	2,870	3,684	25,024

Source: Elaboration on ISTAT data, 2022.

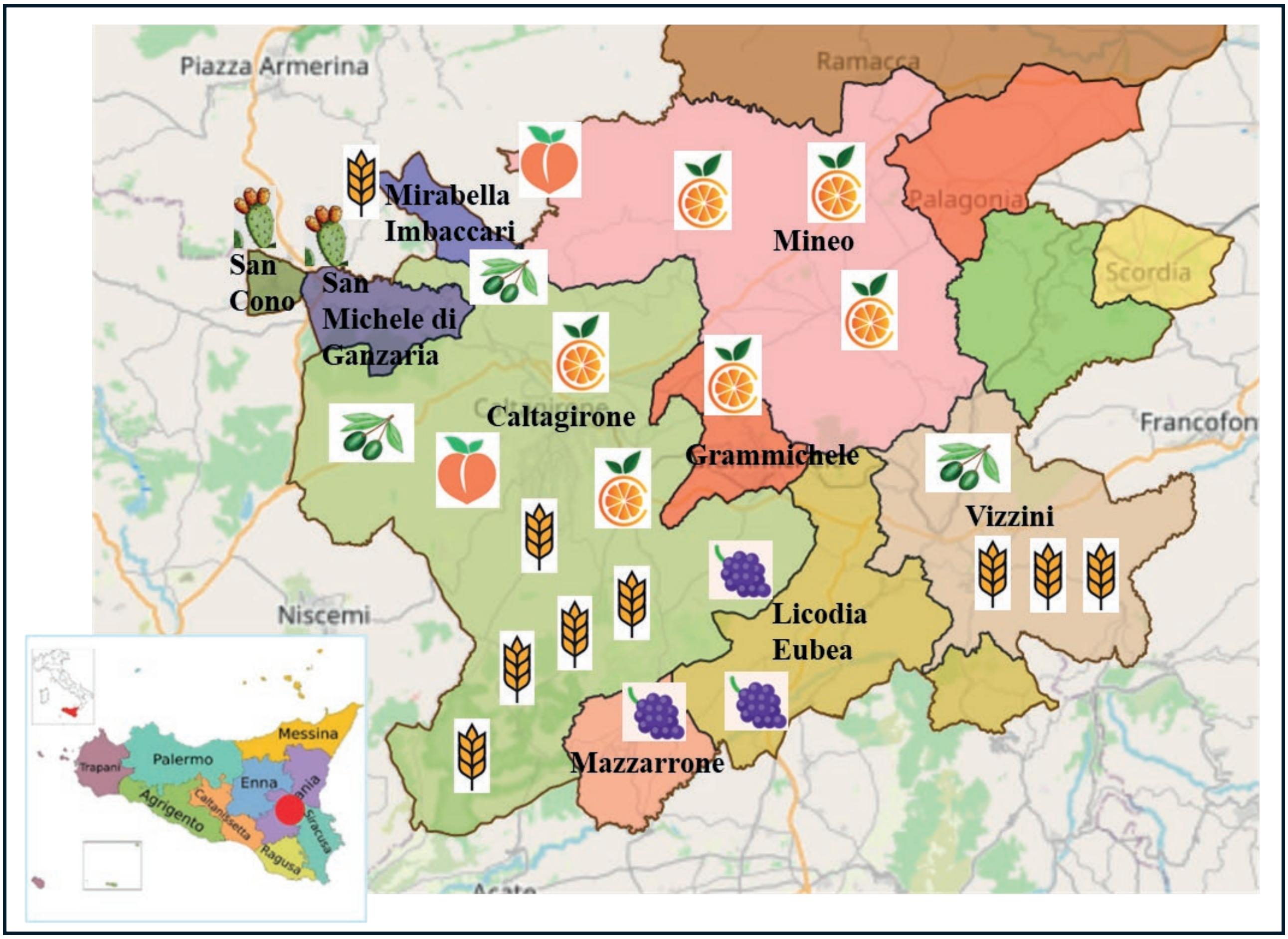

Figure 1. Production characteristics of the study area (our elaboration).

citrus cultivation was chosen as the focal crop for the Living Lab project because of its significant economic weight in the Calatino area and its sensitivity to water resource management issues. Citrus fruits represent one of the main sources of local agricultural income and require particularly efficient water management, making them an ideal case for experimenting with innovative strategies in line with agroecological principles.

The primary objectives are to promote:

- the transition to organic farming and organic certification to enhance the competitiveness of local products;
- the adoption of sustainable agricultural practices, such as crop rotations, organic fertilizers, and integrated pest management, in line with agroecological principles;
- short supply chains, through local markets and the creation of a food hub for the distribution and valorization of organic products;
- social inclusion and cooperation among producers, processors, and distributors.

Through these strategies, the Bio-district aims to enhance the environmental sustainability of local agriculture and promote economic development based on circularity and biodiversity, positioning Calatino as a model for agroecological transition in Sicily.

2.2. Study design

The Calatino Living Lab serves as a participatory platform where farmers, researchers, technical experts, and institutional representatives collaborate to facilitate the agroecological transition of the region. This large-scale transition is often hindered by regulatory constraints, economic challenges, and technological limitations (Toffolini et al., 2021; Beaudoin et al., 2022; Potters et al., 2022; Yousefi and Ewert, 2023; Timpanaro et al., 2024; Gardezi et al., 2024). In Sicily, the recent regional legislation on agroecology (Regional Law No. 21 of 29/07/2021, "Provisions on Agroecology, Biodiversity Protection, Sicilian

Agricultural Products, and Technological Innovation in Agriculture") establishes strict criteria for farms, highlighting the need for an in-depth analysis of its practical implications and potential areas for improvement.

The methodological approach adopted is summarized in Figure 2. The establishment of a collaborative ecosystem is imperative for the co-design of innovative solutions for sustainable water resource management, agroecology, and the adoption of enabling technologies by farmers, institutions, researchers, businesses, and consumers. A preliminary study involved the identification of key stakeholders and the definition of local challenges. This was followed by structuring the Living Lab as a participatory platform for research and experimentation. Stakeholders were selected using a targeted approach, favoring organic or in-conversion farmers operating in the citrus sector who expressed interest in adopting agroecological practices and innovative technologies. Institutional representatives, technicians and local associations with a key role in promoting agricultural sustainability in the Calatino area were also involved. Stakeholder engagement was achieved through preliminary meetings, thematic focus groups, interactive workshops, and demonstration visits to pilot farms, with invitations disseminated via email, social media, and local networks.

Although this targeted selection ensured the active participation of motivated and competent actors, it is important to recognise that it may have introduced a certain degree of bias into the selection. Specifically, the inclusion of stakeholders already inclined towards innovation and sustainability may limit the generalisability of the results to broader agricultural populations that may be more hesitant or resistant to adopting digital technologies.

The first step of the Living Lab was an in-depth analysis of regional regulations to understand the criteria for recognizing agroecological farms and the potential barriers to their adoption. Through participatory discussions among stakeholders several critical issues were identified, including:

– high initial requirements, such as the obligation to allocate 20% of farmed land to native varieties and to replant 20% of the area with indigenous tree species;
– management difficulties, due to the requirement for complex environmental certifications and the high costs of compliance;
– limited technological support, as no incentives are provided for adopting innovative tools that could facilitate the agroecological transition;
– commercial constraints, including the obligation to sell 20% of production in local markets, a requirement that could disadvantage farms located in more remote areas.

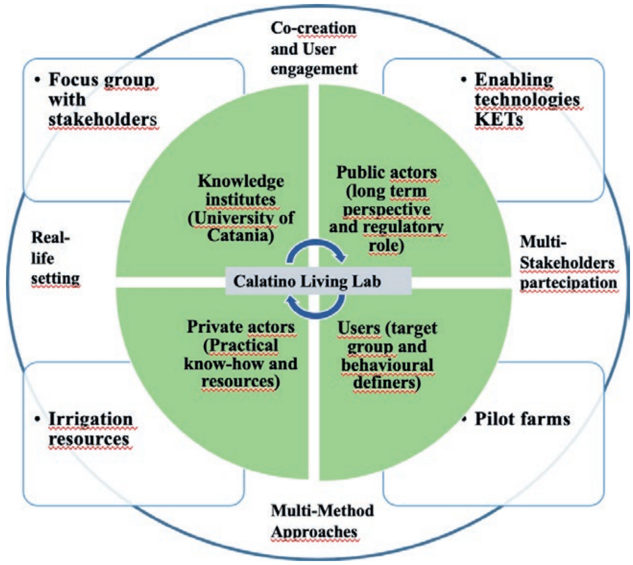

Figure 2. Methodological framework adopted in the Calatino Living Lab.

The stakeholder discussions within the Living Lab also highlighted a shared need to leverage technological innovations to support farms in resource management, improve production efficiency, and ensure economic sustainability. A key concern among stakeholders was water resource management, one of the main challenges for Sicilian agriculture. Multiple focus groups were organized to explore issues such as:

– how can water management be improved in agroecological farms?
– which technologies can promote water conservation without compromising productivity?
– what strategies can be adopted to make irrigation more efficient and less dependent on intensive water use?

The focus groups revealed that many organic farms lack advanced tools for water monitoring, relying instead on empirical practices that often lead to waste or water shortages.

Based on the discussions and emerging needs, two organic citrus farms in the Calatino region were selected as pilot cases to assess the impact of enabling technologies applied to irrigation management (one implementing Key Enabling Technologies and the other without KETs). These farms align with the agroecological principles defined by FAO (2018) and were equipped with (Table 2):

– weather stations for real-time monitoring of temperature, humidity, and precipitation;
– soil sensors to measure moisture levels and optimize irrigation;

– Decision Support Systems (DSS) based on climatic and agronomic data to enhance resource management.

The choice of these technologies was guided directly by the critical issues identified during the focus groups. Soil sensors and weather sheds allow accurate monitoring of environmental parameters, enabling more efficient irrigation management tailored to actual crop needs. The DSS system provides farmers with decision support based on objective data, reducing uncertainty in irrigation planning and helping to limit water wastage. Table 2 summarizes the comparison between the principles of agroecology (FAO, 2018), the corresponding enabling technologies, and their practical application in traditional agroecology, precision agriculture, and the two pilot farms within the Living Lab. The structure of the table allows for a direct comparison of how different approaches integrate technology to address agroecological goals. Reading across each row, one can observe the progressive transition from traditional practices to precision and digitally-supported agroecological farming. Each principle – such as biodiversity, resource efficiency or co-creation of knowledge – is linked to specific digital tools (e.g. soil sensors, DSS platforms) and corresponding practices observed in the field. For example, while the traditional approach relies on experience-based decisions, the digitised farm uses real-time data to manage irrigation and nutrient input more precisely. This alignment between agroecological objectives and enabling technologies illustrates how innovation can improve sustainability and productivity without compromising ecological integrity.

2.3. Elaboration method

The comparison between citrus farming with and without innovative technologies was based on the analysis of total costs and net benefits for each system, includ-

Table 2. Comparison between Agroecology, Precision Agriculture and the two pilot citrus farms for experimentation within the Calatino Living Lab.

FAO principles	Enabling technologies	Agroecology	Precision agriculture	Farm with technologies	Farm without technologies
1. Diversity	GIS (Geographic Information Systems)	Biodiversity mapping	Irrigation and fertilization zoning	Mapping cover crops and water retention	Traditional cultivation without mapping
2. Synergy	Big Data	Local agroecological planning	Optimization of production efficiency	Weather and soil data analysis for crop synergy	Experience-based management and traditional rotations
3. Efficiency	IoT (Internet of Things)	Sensors for water conservation	Automated irrigation and fertilization	Targeted irrigation sensors and DSS for water management	Scheduled irrigation without monitoring
4. Resilience	Drones	Monitoring of natural resources	Detection of infestations and targeted irrigation	Decision-support system for mitigating water and climate stress	Reactive response to climate change without predictive tools
5. Recycling	Sensors	Natural measurement of soil nutrients	Advanced soil and crop monitoring	Nutrient monitoring to reduce chemical inputs	Fertilizers and compost application based on experience
6. Knowledge Sharing	Big Data and digital platforms	Shared access to environmental and agricultural data	AI-driven process optimization	Software for comparison between agroecological farms	Limited knowledge exchange within local cooperatives
7. Human and Social Values	Mobile applications for farmers	Digital training for social inclusion	Agricultural workforce automation	Decision-making support based on digital data	Dependence on personal experience and manual labor
8. Food Traditions	Blockchain for traceability	Protection of local production	Monitoring of production chains	Traceability of farm sustainability	Traditional sales without digital certification
9. Responsible Governance	Open data and GIS	Active participation in agricultural management.	Automated data collection for agricultural policies	Use of platforms for farm monitoring	Participation limited to local cooperatives
10. Circular Economy	IoT and AI for agricultural waste management	Recycling and reuse of agricultural by-products	Waste reduction through optimization	Crop residue recovery and reuse of wastewater	Traditional disposal without optimization

ing water savings, production yield, and profitability increase, as extensively explored in the literature (Alston, 2010; Pardey et al., 2010; Lubell et al., 2011; Alston et al., 2021; Medici et al., 2021; Jamil et al., 2021).

The baseline assumptions for the comparison are reported in Table 3. The analyzed parameters highlight the potential impact of digital innovations on irrigation, climate monitoring, decision-making processes, water-use efficiency, management costs, and agronomic yield.

As for the total costs (C) for each agricultural system, these are calculated as the sum of the costs of water, fertiliser, labour, cover crops and technology (for the innovative system only), as shown in Table 4.

The additional benefit of farming with innovative technologies over conventional farming is given by:

$$\Delta B = \Pi_t - \Pi_c$$

Expanding

$$\Delta B = A*((P_t - P_c) \bullet p - \ [(W_t - W_c)*C_w + C_t + C_{cc}])$$

where:
$(P_t - P_c) * p$ = represents the increase in profitability due to increased production.
$(W_t - W_c) * C_w$ = represents the water savings in terms of costs.
$C_t + C_{cc}$ are the additional costs for the adoption of technologies and cover crops.

If:
$\Delta B>0$ → adoption of the technologies is cost effective.
$\Delta B<0$ → the additional costs outweigh the benefits, making the transition uneconomic without incentives.
$\Delta B \approx 0$ → Profitability is similar in the two models, but there may be indirect environmental benefits.

The economic evaluation was completed with a sensitivity analysis, hypothesising alternative scenarios on a possible rent for the KETs plant and equipment (necessary to have up-to-date and enhanced decision support systems with links to meteorological databases), and with a Monte Carlo modelling to focus the analysis on the other variables (water consumption, operating costs, production) that present uncertainty and that most influence the difference in profit between the two pilot companies.

Monte Carlo modelling assumes that:

$$\Delta\Pi_i = \Pi_i^{tech} - \Pi_i^{nontech}$$

At the end of N iterations we estimate

- the average profit for each company

$$\overline{\Pi}^{tech} = \frac{1}{N}\sum_{i=1}^{N}\Pi_i^{tech} \text{ and } \overline{\Pi}^{nontech} = \frac{1}{N}\sum_{i=1}^{N}\Pi_i^{nontech}$$

- the average difference

$$\overline{\Delta\Pi} = \frac{1}{N}\sum_{i=1}^{N}\overline{\Delta\Pi}_i$$

- the distribution (and dispersion) of $\Delta\Pi$, which makes it possible to assess the probability that the technology will lead to a higher profit.

The final Monte Carlo model used was as follows:

$$\Delta\Pi = \left[400*/\mathrm{Q}^{\mathrm{tech}} - \left(\mathrm{w}*/\mathrm{c}_{\mathrm{w}}^{\mathrm{tech}} + /\mathrm{c}_{\mathrm{cover}}^{\mathrm{tech}} + /\mathrm{c}_{\mathrm{fert}}^{\mathrm{tech}} + /\mathrm{c}_{\mathrm{pest}}^{\mathrm{tech}} + /\mathrm{c}_{\mathrm{energy}}^{\mathrm{tech}} + /\mathrm{c}_{\mathrm{tech}} + /\mathrm{c}_{\mathrm{other}}\right)\right] - /\left[400*/\left(\mathrm{w}*/\mathrm{c}_{\mathrm{w}}^{\mathrm{nontech}} + /\mathrm{c}_{\mathrm{cover}}^{\mathrm{nontech}} + /\mathrm{c}_{\mathrm{fert}}^{\mathrm{nontech}} + /\mathrm{c}_{\mathrm{pest}}^{\mathrm{nontech}} + /\mathrm{c}_{\mathrm{energy}}^{\mathrm{nontech}} + /\mathrm{c}_{\mathrm{other}}\right)\right]$$

where each uncertain parameter is sampled from a specified distribution. Repeating this calculation for many

Table 3. Comparison parameters adopted in the evaluation of KETs in citrus fruit growing.

Aspect	Farm with technology	Farm without technology
Irrigation	Uses precise data (soil moisture, weather forecasts) to optimize water requirements	Irrigation based on experience and traditional fixed irrigation cycles (not optimized)
Climate monitoring	Weather station and sensors provide real-time data on temperature, wind, and rainfall	Based on visual observations and generic weather forecasts
Decision-making	User-friendly application suggests irrigation timing and quantity	Subjective decisions based on intuition and experience
Water efficiency	Greater water control with reduced waste	High risk of water excess or deficit, leading to higher-than-necessary consumption
Management costs	Initial investment in technology, but lower variable costs (e.g., energy for irrigation)	Constant costs due to inefficient resource use
Agronomic yield	Optimized water requirements and reduced plant stress, leading to higher productivity	Yield affected by irrigation mismanagement or unexpected climatic conditions

Source: Our elaboration.

Table 4. Data determination methodology for evaluating the cost-effectiveness of adopting KETs technology for water savings.

Variables	Farm with Technology	Farm without Technology
Total costs (C)	$C_t = A^*(W_t{}^*C_w + C_f + C_p + C_t + C_e + C_{cc} + C_{other})$	$C_c = A^*(W_c{}^*C_w + C_f + C_p + C_e + C_{cc} + C_{other})$
Total revenue (R)	$R_t = A^*P_t{}^*p$	$R_c = A^*P_c{}^*p$
Net profit (Π_c)	$\Pi_t = /R_t - /C_t = A^*(P_t{}^*p - (W_t{}^*C_w + /C_f + /C_p + /C_t + /C_e + C_{cc} + /C_{other}))$	$\Pi_c = /R_c - /C_c = A^*(P_c{}^*p - (W_c{}^*/C_W + /C_f + /C_p + /C_e + /C_{cc} + /C_{other}))$

The variables considered were the following: A = Cultivated area (ha); Pc = Production per hectare in agriculture without innovative water-saving technologies (t/ha); Pt = Production per hectare in agriculture with innovative water-saving technologies (t/ha); p = Sales price per tonne (€/t); Wc = Water consumption per hectare in agriculture without innovative water-saving technologies (m^3/ha); Wt = Water consumption per hectare in agriculture with innovative water saving technologies (m^3/ha); Cw = Water cost per m^3 (€/m^3); Cf = Fertiliser cost per hectare (€/ha); C_p = Pesticide cost per hectare (€/ha); Ct = Technology cost (installation + maintenance per hectare) (€/ha); Ccc = Cover crop cost per hectare (€/ha); C_e = Energy cost per hectare (€/ha); C_{other} = Other costs (€/ha).

iterations yields the profit difference distribution, which provides a comprehensive assessment of the economic sensitivity to the adoption of the innovative technology.

3. RESULTS

3.1. Living Lab approach and case study characteristics

The two citrus farms analyzed were identified as pilot sites within the Living Lab of the Calatino Inner Area, a collaborative ecosystem aimed at testing and validating innovative solutions for regenerative citrus farming and sustainable water resource management. The objective is to develop scalable strategies for other farms seeking to integrate regenerative practices with technological innovations.

The selection of the farms (Table 5) was based on:

- Representation of the citrus sector within the region and the study area.
- Diversity in management practices, as one farm adopted enabling technologies, while the other relied on a traditional agroecological approach.
- Entrepreneurs' willingness to engage in the co-experimentation and training process.

The two pilot farms are in Mineo (Catania province) and share the same production identity (5 hectares of blood oranges, organic certification, and a commitment to regenerative agriculture). Their differing agricultural management approaches make them suitable case studies for assessing the impact of enabling technologies compared to a system based solely on traditional agronomic experience.

The farm utilizing innovative technology has integrated sensors, a decision support system (DSS), and advanced soil analysis to optimize irrigation and plant nutrition. The goal is to achieve more efficient water use, a more targeted nutrient management strategy, and continuous pest monitoring, thereby reducing input usage and maximizing productivity.

The farm without innovative technology follows a more traditional approach, with manually scheduled irrigation and fertilization based on the farmer's experience. While it employs cover crops and organic farming strategies, it lacks tools for real-time monitoring of soil and water conditions, which can result in less precise management and higher resource consumption.

The intersection of three key elements – organic farming (a low-impact agricultural management model aligned with agroecological principles, aiming for balanced and resilient production systems while reducing dependency on external inputs), regenerative agriculture (cover crops contribute to reducing erosion, improving water retention, and increasing soil organic matter, fostering a healthier and more productive ecosystem in the long term), and enabling technologies (agroecology does not exclude technology but leverages it to enhance sustainable resource management) – is represented by agroecology. This guiding principle unites the two pilot farms of the Living Lab in the Calatino.

This integrated approach improves the sustainability, productivity, and resilience of agricultural systems, turning environmental and economic challenges into opportunities for innovation (Niggli, 2015; Gascuel-Odoux et al., 2022; Bless et al., 2023; Domínguez et al., 2024).

3.2. Issues related to the management of irrigation resources

The discussion among stakeholders on the water emergency in citrus farming has highlighted how it is the result of a combination of climatic, institutional and economic factors that negatively affect production and farm sustainability. Figure 3 represents a visualization of the relationships between the main factors character-

Table 5. Structural characteristics of the pilot sites.

Information	Farm with technology	Farm without technology
Localization	Mineo	Mineo
UAU, ha	5	5
Production address	Blood orange	Blood orange
Organic certification	Yes	Yes
Regenerative agriculture	Cover crops + advanced water management	Cover crops with traditional management
Water use	Sensor monitoring + DSS	Manually programmed irrigation
Nutrient management	Soil analysis + targeted fertilisation	Experience-based fertilisation
Pest control	Biological strategies + data monitoring	Biological strategies without monitoring
Market	Selling to local supply chains and quality markets	Selling to local supply chains and quality markets

Source: Our elaboration.

izing this crisis, as they emerged during the focus group. The structure was elaborated using MAXQDA software, through the exploration of co-occurrences between thematic codes applied to text segments. The figure is organized hierarchically, starting from the main cause (climate change) at the top, branching downward into its effects on water availability and plant health, and further into institutional and economic consequences. Arrows represent causal links, while mitigation strategies are shown as side branches connected to the specific problems they address. No color coding was used; the structure is entirely based on logical connections and thematic clusters. This approach made it possible to clearly highlight the connections between climatic, institutional and economic variables, as well as the mitigation strategies adopted by citrus growers and sector experts.

The central element of the water crisis, as emerged from the discussion, is climate change, which manifests through alterations in rainfall patterns. This results in two opposing but equally damaging situations: water scarcity, caused by reduced precipitation and rising temperatures that intensify evaporation and increase plant water demand, or water excess, with sudden and intense rainfall leading to floods, water stagnation, and root damage.

These issues are compounded by institutional inefficiency, which worsens water resource management. The lack of maintenance of watercourses, poor planning in water distribution, and the bureaucratic rigidity of reclamation consortia make it difficult for citrus growers to access water when they need it most. Additionally, the absence of a consumption-based pricing system leads to waste and inefficient resource use.

To address the water crisis, citrus growers have adopted various technological and agronomic solutions. These include innovations in irrigation, such as surface and subsurface micro-irrigation systems to reduce water waste, or the use of regulated deficit irrigation systems to optimize

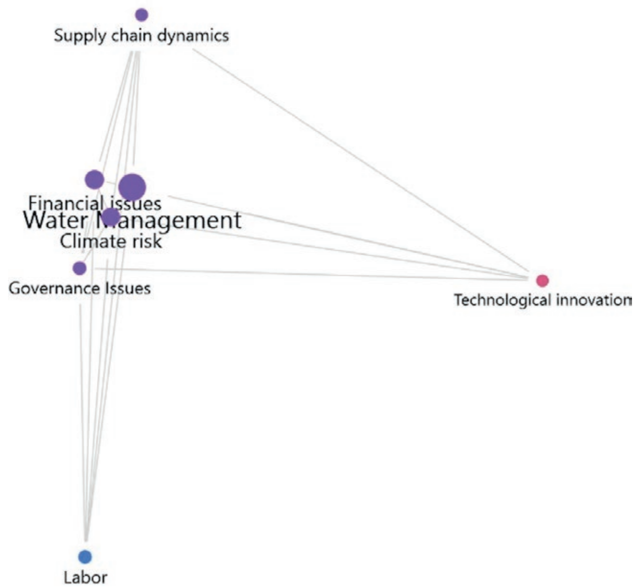

Figure 3. Cause-effect relationships in irrigation water management issues in citrus farming

water use according to plant growth stages. Farmers have also experimented with alternative water resources, such as treated wastewater, through phytoremediation processes, to reduce dependence on conventional water sources. A common strategy is the selection of rootstocks resistant to water stress, as well as the use of raised beds to improve drainage and controlled cover cropping.

According to stakeholders, a coordinated territorial approach involving public institutions, reclamation consortia, and producer organizations is lacking. Additionally, a revision of irrigation tariffs based on actual consumption could encourage more responsible water use, while increased digitalization in water resource management (sensors, weather stations) could enable more precise irrigation planning.

Table 6. Parameters for comparing citrus fruit farms with and without KETs.

Parameter	Farm with technology	Farm without technology	Difference %
Annual water consumption (m^3/ha)	2,800	4,200	-33%
Average cost of water (€/m^3)	0.3	0.3	0%
Water saving (€/ha)	420 €	0 €	---
Water saving (%)	33%	0	---
Production per hectare (t/ha)	44	38	16%
Sale price (€/t)	400 €	400 €	0%
Revenues per hectare (€/ha)	17,600 €	15,200 €	16%
Cost cover crops (€/ha)	250 €	250 €	---
Fertiliser costs (€/ha)	720 €	850 €	-15%
Pesticide cost (€/ha)	40 €	140 €	-71%
Energy cost for irrigation (€/ha)	520 €	750 €	-31%
Technology investment (€/ha)	500 €	0 €	---
Other cost	1,570€	1,990€	-21%
Total cost (€/ha)	3,600 €	3,980 €	-10%

Source: Our elaboration.

These results highlight not only the complexity of the water crisis, but also the proactive role of farmers in experimenting with feasible solutions. The issues and strategies discussed in this section have been translated into the visual structure shown in Figure 3, which helps to summarise the entire problem-solving framework in a single view. This makes the figure particularly useful for better understanding where to intervene and how to support adaptation efforts more effectively.

3.3. Cost-effectiveness assessment of KETs deployment

The calculations clearly show the positive impact of KET adoption on farm management, with benefits reflected in water efficiency, operating costs, productivity and overall profitability.

Table 6 shows that the adoption of enabling technologies results in a significant improvement in farm management, with water consumption reduced by 33% and a consequent annual saving of 420 €/ha, without penalizing productivity. This implies greater sustainability in resource use and reduced production costs.

The cost of energy for water withdrawal is reduced by 31%, confirming how energy efficiency is an additional economic benefit of technological innovation.

Productivity increases by 6 tons/ha (+16%), translating into a revenue increase of €2,400/ha. This result underscores how technological adoption not only improves efficiency, but also directly contributes to strengthening the company's competitiveness.

At the same time, there is a reduction in the use of fertilizers (-15%) and a drastic decrease in pesticides (-71%), reflecting the improvement in agronomic management and less dependence on external inputs, with clear economic and environmental benefits.

Table 7. Comparison of economic benefits and adoption convenience between citrus farms with and without KETs.

Parameter	Farm with technology	Farm without technology	Difference %
Revenues R (€/ha)	17,600 €	15,200 €	16%
Total costs C (€/ha)	3,600 €	3,980 €	-10%
Net profit Π (€/ha)	14,000 €	11,220 €	25%
Change in benefits (ΔB)	+2,780		

Source: Our elaboration.

Despite an initial investment of €500/ha, the innovative company achieves a net profit of €14,000/ha, compared to €11,220/ha for the traditional company, with a 25% increase in profitability (+€2,780/ha) (Table 7). This highlights how the economic benefits far outweigh the costs of technology adoption.

3.4. Sensitivity analysis

Considering three scenarios based on complete enabling technologies to be acquired by annual subscription, a sensitivity analysis can also be developed (Table 8):

– 200 €/ha/year → Basic Package (sensors + basic software);
– 400 €/ha/year → Intermediate (sensors + advanced DSS + local weather)

Table 8. Profit sensitivity with technology rent.

Rental scenario	Annual cost per hectare (€)	Net new profit (€/ha)	Difference vs. farm without technology (€)	Convenience compared to the traditional model
Rent 200 €/ha/year	200.00 €	13,800.00	2,580.00	Very affordable
Rent 400 €/ha/year	400.00 €	13,600.00	2,380.00	Still profitable
Rent 600 €/ha/year	600.00 €	13,400.00	2,180.00	Advantageous but low margin

Source: Our elaboration.

– 600 €/ha/year → Advanced (sensors + advanced DSS + weather integrated with weather databases such as SIAS, ISPRA, SwissMetNet, etc.).

Sensitivity analysis on the different levels of technology subscription shows that even with a higher fee (600 €/ha/year), the positive margin remains substantial (+2,180 €/ha compared to the farm without technology). The intermediate package (400 €/ha/year) emerges as the one most balanced between investment and economic benefit, suggesting a sustainable option for maximizing farm profitability.

To assess how net profit (€/ha) responds to key economic drivers, a Monte Carlo simulation was conducted. The goal was to compare the farm adopting innovative technology with the one that does not, highlighting how variations in certain parameters can either amplify or reduce the benefits derived from technology adoption.

The model assumed that the product's selling price (400 €/t) and non-specific fixed costs (e.g., general expenses, logistics) remain constant, while variations in production and costs influenced by technology were analyzed. Analysis considered water costs, expenses for cover crops, fertilizers, pesticides, irrigation energy, and, for the technology-adopting farm, the technological investment.

The Monte Carlo simulation involves repeated iterations, where in each cycle, random values are drawn for each parameter according to predefined distributions. In this study, uniform distributions around baseline values were assumed. In particular, the unit cost of water was varied between 0.3 and 0.5 €/m^3, while water consumption for the technological farm ranged between 2,520 and 3,080 m^3/ha, and for the non-technological farm, between 3,780 and 4,620 m^3/ha. Similarly, production per hectare and operating costs were defined within specific intervals to reflect real-world variability and simulate a wide range of scenarios.

Table 9 shows that, on average, the farm adopting technology achieves a net profit of approximately 14,000 €/ha, while the non-technological farm reaches around 11,220 €/ha, resulting in an average difference of +2,780 €/ha. These results indicate a significant average economic benefit from adopting innovative technology. The standard deviations, 1,200 €/ha and 1,400 €/ha respectively, highlight considerable variability. This suggests that while the average benefit is positive, in some scenarios, the advantage may be lower or even more pronounced.

Table 9. Monte Carlo simulation results.

Statistics	Farm with technology (€/ha)	Farm without technology (€/ha)	Difference (Tech - NonTech, €/ha)
Average profit	14.000 €	11.220 €	2.780 €
Standard deviation	1.200 €	1.400 €	1.300 €
Minimum Profit	11.000 €	8.500 €	2.500 €
Maximum profit	17.000 €	15.500 €	3.500 €
Median	14.100 €	11.300 €	2.800 €

Source: Our elaboration.

The economic advantage is primarily driven by savings in operational costs. The technology enables a substantial reduction in water consumption, leading to lower water expenses, and decreases costs associated with fertilizers and pesticides, due to more efficient and sustainable farming practices. These savings, combined with a potential increase in yield per hectare, contribute to a higher net profit.

The simulation also highlights the model's sensitivity to various parameters. For instance, an increase in the unit cost of water shifts total costs to higher values, making water savings even more critical. Similarly, variations in yield per hectare directly affect revenue and, consequently, net profit. The ability to adjust multiple parameters simultaneously helps identify key drivers of economic success and potential sources of risk.

The Monte Carlo simulation comparing farms with and without innovative technology demonstrates that adopting technology leads to a significant average increase in net profit per hectare. These findings provide essential support for strategic decision-making in a competitive and dynamic environment, where operational efficiency and innovation are crucial for success.

4. DISCUSSION

The analysis conducted within the Living Lab of the Calatino inner area has enabled an exploration of the impact of enabling technologies on the agroecological transition in inner areas, highlighting economic, environmental, and organizational benefits. Starting from the research questions, the findings clearly show that the integration of enabling technologies enhances the efficiency of resource management, particularly in terms of water and nutrient use, helping to improve productivity and keep costs down. These findings align with those reported by Bellon-Maurel et al. (2022) and Maurel and Huyghe (2017), who highlight how digital tools contribute to resource optimization and improved sustainability in agricultural systems. Furthermore, Ajena et al. (2022) emphasize that digitalization can break down traditional barriers fostering innovation in rural sectors, particularly in inner areas where challenges are more pronounced. Therefore, the integration of technology accelerates the agroecological transition by providing farmers with real-time data and decision-making tools that enhance precision and sustainability in farm management. Regarding the second research question, the comparison between the two pilot farms revealed a significant gap in farmers' perceptions. The farm that adopted the innovative technology reported tangible benefits, such as reduced operational costs and improved productivity. In contrast, the farm following a traditional approach relied on well-established methods and expressed skepticism toward digital tools. This resistance stems from a perception of greater reliability associated with traditional methods, combined with limited familiarity with innovative technologies and concerns about high initial costs and a steep learning curve. These aspects are consistent with the findings of Anderson and Maughan (2021) and Schiller et al. (2020), who describe the existing gap between innovation and tradition in agriculture. Literature suggests that the lack of specific training and institutional support represents a major barrier to the adoption of digital technologies (Timpanaro et al., 2023).

In this context, Living Labs serve as co-experimentation and training spaces that facilitate knowledge transfer and help overcome initial resistance (Scuderi et al., 2023). Active participation and dialogue among farmers, researchers, and technical experts contribute to demystifying new technologies and highlighting their potential in sustainable resource management. Living labs show that they can function as catalysts for change, fostering an agroecological transition that is not only technologically advanced, but also socially inclusive (Cascone et al., 2024; Beaudoin et al., 2022).

The third research question led to a deeper analysis and reflection on the economic outcomes through Monte Carlo simulation. From an economic perspective, the farm integrating enabling technologies achieves higher per-hectare revenues due to increased production and more efficient cost management. These findings align with the studies of Alston (2010) and Pardey et al. (2010), which emphasize how agricultural innovation can generate substantial economic benefits.

From an environmental perspective, the adoption of innovative technologies promotes more sustainable resource management and a reduction in chemical input use. The decrease in water consumption and pesticide application, for example, contributes to minimizing environmental impact and fostering more regenerative agricultural practices. These results are consistent with the evidence provided by Domínguez et al. (2024) and D'Annolfo et al. (2017), who highlight the potential of combining agroecological practices with technological innovation to promote sustainable and resilient agriculture. Thus, the integration of technologies not only enhances economic efficiency but also represents a successful approach to reducing environmental impact by encouraging a more responsible use of resources.

Finally regarding Q4, the Living Lab model implemented in the Calatino context has proven to be an effective environment for the co-creation and experimentation of innovative solutions. The two pilot farms, despite sharing the same production identity and organic certification, differ in their management approach: one integrates enabling technologies, while the other follows a traditional method. This strategic choice has highlighted how the presence of digital technologies is not contradictory to agroecological principles but rather enhances their effectiveness, improving the sustainable management of resources and the resilience of the production system.

Living Labs play a crucial role in bridging the gap between technological innovation and traditional agricultural practices. They provide a space where farmers, researchers, technologists, and institutional stakeholders can experiment, exchange experiences, and validate solutions in real time (Scuderi et al., 2024). In our case, the adoption of digital tools has improved irrigation monitoring and management, leading to more efficient water use and lower operational costs. These results, combined with the integration of regenerative practices such as the use of cover crops and targeted nutrient management, contribute to creating an integrated system that addresses the environmental and economic challenges of inner areas. Moreover, the active participation of farmers in Living Labs fosters a bottom-up approach that stimulates responsible innovation and the dissemination of best practices.

For example, during one of the demonstration sessions, an organic farmer had the opportunity to test a low-cost soil moisture monitoring system, immediately noting its usefulness in reducing water waste. This kind of direct experience helped turn initial prejudice into interest and openness. In another case, a young farmer who initially showed skepticism toward the use of digital data for crop management changed his perspective after sharing his needs with a group of experts within the Living Lab and receiving support in interpreting the data collected. The opportunity to learn by doing, in a nonjudgmental and co-creation-oriented context, proved essential to reduce cognitive barriers and build confidence toward innovation. Recent studies (Gascuel-Odoux et al., 2022; Potters et al., 2022) also highlight how collaboration and the engagement of local actors are essential for achieving effective and sustainable agroecological transitions.

A critical issue that deserves attention concerns the economic implications related to the costs of adopting enabling technologies, especially in vulnerable rural settings. While these technologies can generate efficiency and reduced operating costs, they often entail significant upfront investments, the need for technical maintenance, and increasing dependence on external suppliers. This can lead to an imbalance in bargaining power between farms, which are often small or medium-sized, and technology providers, which operate according to industrial and centralized market logics.

In the absence of adequate support and regulatory measures, this imbalance can produce regressive effects: farms with greater economic capacity will be able to access technologies more easily and take competitive advantage of them, while the more fragile realities risk being excluded from the innovation process (Bissadu et al., 2025).

For this reason, it is crucial to accompany technology adoption with targeted policy strategies capable of ensuring affordability, technical training, systems interoperability and open innovation models. Living Labs, represent a possible lever to rebalance power dynamics through co-design and direct involvement of farmers in technology selection and testing processes. To effectively address these power imbalances and promote a more inclusive adoption of enabling technologies, several targeted policy actions should be considered. Such measures can help rebalance contractual relationships between farmers and technology providers, in line with the principles of responsible innovation (Bellon-Maurel et al., 2022; Beaudoin et al., 2022; Gava et al., 2025).

First, public incentives for technology adoption should be conditional on the use of open standards and interoperable systems to avoid technological lock-in, as discussed by Ditzler and Driessen (2022) and Clapp and Ruder (2020). This approach strengthens farmers' autonomy and prevents dependence on proprietary technologies controlled by a few large suppliers (Bissadu et al., 2025).

Second, it is essential to promote the creation of farmer-led cooperatives or technology consortia to strengthen collective bargaining power in the purchase and negotiation of technology services. This is in line with recommendations to strengthen agricultural innovation systems (Potters et al., 2022) and enable bottom-up governance models (Gava et al., 2025).

Thirdly, the creation of public platforms dedicated to the collective procurement of technologies, supported by technical advisory services and independent consultants, can further protect farmers from unfavourable contractual conditions. The provision of advisory vouchers for access to third-party technical expertise would complement this strategy.

Furthermore, regulatory frameworks should explicitly recognise farmers' ownership of agricultural data generated by digital systems, ensuring that technology providers cannot appropriate or monetise such data without informed consent (Clapp and Ruder, 2020; Bellon-Maurel et al., 2022).

Living Labs themselves can be institutionalised as territorial "technology brokers", acting as independent intermediaries to ensure equitable access to innovation and promote co-created solutions tailored to local needs (Beaudoin et al., 2022; Gardezi et al., 2024). This model of participatory innovation is in line with the agroecological governance structures advocated by Gascuel-Odoux et al. (2022), which support equitable access to technological innovation in rural areas.

By adopting these integrated strategies, policymakers can help reduce asymmetries in bargaining power, protect the interests of smallholder farmers, and promote an inclusive, resilient, and participatory agroecological transition.

In summary, our research findings indicate that:

- The integration of enabling technologies accelerates the agroecological transition by improving resource management and increasing profitability.
- Farmers' perceptions are influenced by direct experience and the support provided by Living Labs, which help overcome resistance to innovation.
- The combination of agroecological practices and innovative technologies generates positive economic and environmental impacts, as evidenced by increased productivity and reduced operational costs.
- Living Labs play a key role in facilitating the integration of technology and agroecology, fostering the

creation of integrated and sustainable systems in inner areas.

These findings not only confirm the existing literature but also provide an operational framework to guide strategic decisions in complex agricultural contexts, where sustainability and innovation need go hand in hand. The integrated and participatory approach promoted by Living Labs thus emerges as an effective response to current and future challenges, helping to transform environmental and economic challenges into opportunities for innovation and sustainable development.

5. CONCLUSIONS

The study conducted within the Living Lab of the Calatino Inner Area highlights how the integration of enabling technologies can play a crucial role in accelerating the agroecological transition in rural areas. The results, derived from a comparative analysis of two pilot citrus farms – one adopting advanced digital tools and the other maintaining a traditional approach – demonstrate economic, environmental, and managerial benefits, confirming the transformative potential of such innovations.

The farm that integrated sensors, decision support systems (DSS), and other digital technologies achieved significant operational efficiency, including a 33% reduction in water consumption and a 16% increase in yield per hectare, leading to a 25% improvement in profitability. These findings not only underscore the importance of more precise resource management but also confirm that the adoption of enabling technologies can enhance environmental sustainability by reducing chemical inputs and improving irrigation efficiency. The study also highlights some critical issues and concrete challenges to be addressed. Among these, the affordability of technologies is a major obstacle, especially for small companies with limited liquidity. Similarly, the technical complexity of the systems and the costs associated with maintenance, software updates and staff training may limit widespread adoption. Furthermore, the scalability of the tested solutions remains to be verified in different contexts due to soil and climate conditions, farm size and crop type.

However, this study has some limitations. First, the small number of cases analyzed may limit the generalizability of the results. Given the diversity of agronomic and socio-economic contexts, further large-scale studies are needed to confirm the replicability of the observed benefits. Additionally, while the methodology integrates an in-depth economic analysis and a Monte Carlo simulation, it could be enriched by further long-term measurements to assess the economic and environmental sustainability of these technologies over time.

Another limitation concerns the analysis of farmers' perceptions. While the comparison between the innovative and traditional groups highlighted resistance and scepticism toward digital tools, a more extensive qualitative investigation – such as in-depth interviews or focus groups with a broader sample of producers – could provide further insights into the dynamics of adoption and the training needs required to support the transition.

Based on these considerations, several future research directions emerge. Expanding the Living Lab model to other rural areas in Sicily and different agricultural sectors could help determine whether enabling technologies can generate similar benefits in different contexts. Future studies could implement comparative pilot projects in different production systems, such as viticulture or olive growing, and monitor key indicators like water use efficiency, yield performance, and farmer adoption rates over at least three growing seasons.

Further research could also explore the long-term impact of adopting digital tools, analyzing, for example, how economic and environmental benefits evolve over multiple production cycles and under changing climatic and market conditions. Longitudinal studies should be conducted, integrating detailed farm accounting records, soil and water monitoring data, and farmer surveys, to track both economic returns and resource use efficiency over a 5–10 year horizon. Another key area of interest involves the development of training programs and institutional support mechanisms to facilitate the dissemination of these technologies among farmers. Future initiatives should design modular, practice-oriented training programs focused on digital literacy, irrigation management, and precision agriculture tools, targeting different farmer profiles (smallholders, young farmers, cooperatives), possibly through partnerships with vocational training institutes and local cooperatives. Collaborations with universities and research centers to design dedicated training programs could help overcome learning curve challenges and promote greater adoption of digital systems.

Finally, the study highlights the importance of targeted policy actions to mitigate power asymmetries between farmers and technology providers. By introducing conditional incentives, promoting collective procurement mechanisms, supporting open innovation models, and formalising the role of Living Labs as technology intermediaries, policymakers can help ensure that the digital transformation in agriculture promotes autonomy, inclusiveness, and long-term sustainability (Clapp and Ruder, 2020; Bellon-Maurel et al., 2022; Gava et al., 2025). These measures are essential to enable a fair and balanced agroecological transition, particularly in vulnerable rural contexts.

This study demonstrates that the integration of enabling technologies, supported by a participatory model such as the Living Lab, represents a fundamental driver in accelerating the agroecological transition in rural areas. Despite certain limitations, the findings provide a strong scientific and operational contribution, suggesting that the combination of digital innovation and agroecological practices can not only enhance economic efficiency and environmental sustainability but also foster cultural and organizational change toward a more resilient and inclusive agricultural system. Future research and targeted policy interventions will be essential to facilitate the broader adoption of these models and contribute decisively to the transformation of the agri-food system.

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Consumer intentions to purchase organic pasta with blockchain-based traceability

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Abstract. The increasing complexity of global food supply chains has heightened consumer concerns about food safety, quality and authenticity, and triggered a growing demand for transparency-enhancing technologies such as blockchain. This study examines the factors influencing consumers' intention to purchase organic pasta with blockchain-based traceability using an extended Theory of Planned Behaviour (TPB) framework. In addition to the traditional TPB constructs, the study incorporates trust in quality certifications and attitudes towards blockchain technology to provide a comprehensive analysis of decision-making processes. The data was collected via an online survey of 190 Italian respondents and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results show that subjective norms, perceived behavioural control and attitudes towards technology significantly influence purchase intentions, while trust in quality certifications and attitudes towards the traceability of blockchain do not significantly influence purchase intention.. These findings suggest that while blockchain technology is recognised for its potential to improve transparency, its practical benefits are not yet fully understood or appreciated by consumers. This study contributes to the literature on consumer behaviour in the agri-food sector and provides practical insights for policy makers and marketers to promote blockchain-based traceability systems.

Keywords: consumer purchase intention, theory of planned behaviour (TPB), organic pasta, blockchain-based traceability, food fraud, technology.

1. INTRODUCTION

In the food sector, issues such as traceability and food safety have become central to the supply chain, with producers increasingly prioritising these aspects over other objectives (Alshehri, 2023). This shift goes hand in hand with an emerging paradigm shift in consumer demand. Consumers are now showing an increasing preference for products that are perceived as safer (Mahsun et al., 2023). This is evidenced by the fact that more and more consumers are expressing concerns about food safety and quality and, therefore, favour foods whose labels provide clear and accurate information about product characteristics (Lewis & Grebitus, 2016; Sadílek, 2019; Moru-

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zzo et al. 2020; Kaczorowska et al. 2021). The European Parliament and the Council have also established quality certification for organic agri-food products through Regulation (EU) No 2018/848. According to this Regulation, organic products have been developed to respond to a specific market where consumers demand products whose production respects the environment and animal welfare, preserves biodiversity and contributes to rural development (Sampalean, et al., 2021). However, consumers cannot verify credence attributes and must therefore rely on the reliability of the manufacturer's or retailer's claims (Plasek and Temesi 2019). Credence attributes refer to product characteristics that consumers cannot directly verify before purchase and must rely on external assurances to assess their validity (Plasek and Temesi, 2019; Lassoued and Hobbs, 2015). In the context of food products, these attributes include factors such as organic certification, geographical origin, sustainability claims, and production methods (Fernqvist and Ekelund, 2014)

The credibility of these parties also depends on consumer trust in the food system, including the regulatory authorities responsible for ensuring food safety and compliance with food labelling regulations (Fernqvist and Ekelund 2014; Lassoued and Hobbs 2015; Meijer et al. 2021).

Trust is a multi-layered concept that is shaped by several factors, including the geographical and temporal distance between the parties involved, cultural norms, the institutional environment and historical events that influence perceptions of food safety and quality (Berg, 2004). Currently, consumer trust in the food system is uncertain, particularly in relation to transparency and authenticity (Frewer, 2017; Wu et al., 2021; Menon et al., 2021) and more generally in relation to perceptions of food safety (Macready et al., 2020; Meijer et al., 2021). The main cause of this trend is the inherent complexity of the food supply chain, which involves a multitude of parties and processes (Hassoun et al., 2020; Reitano et al., 2024) and can lead to food safety issues (Meijer et al., 2021). This decline in consumer confidence has significant consequences, such as the limited effectiveness of certifications and consequently a decrease in potential demand for products with credible attributes, such as origin, production process characteristics and product properties (Marozzo et al., 2022). From a public interest perspective, low trust has negative implications for sustainable development and public health policies that rely on traditional forms of certification to inform consumers about the nutritional and ethical value of products Kjærnes, 2006; Sapp et al, 2009; Hobbs and Goddard, 2015; Kaiser and Algers, 2017). Considering the above-mentioned characteristics of the agri-food production system, it is essential to develop a coherent management system adapted to its specific needs (Gardeazabal et al., 2023). In response to the prevailing concerns in the agri-food sector, a number of technological innovations have emerged to improve and strengthen food traceability. Among these, blockchain technology (BCT) has attracted much attention (Reitano et al., 2024). The emergence of cryptocurrencies has led to the popularisation of BCT, which can be defined as a decentralised and immutable register of information (Gupta and Sadoghi, 2019; Krzyzanowski, Guerra & Boys, 2022). In such a system, all subjects in the chain can access the recorded information at any time, but without the possibility to change a record (Tian, 2017; Zhao et al., 2019; Wünsche and Fernqvist, 2022). This function is suitable for meeting the specific requirements of the food industry and creating a reliable system for tracking the path of a food product from production to consumption. This will make it easier to ensure food safety (Saurabh & Dey, 2021; Mónica Martínez-Castañeda & Fejoo, 2023) and has the potential to combat problems such as label tampering, counterfeiting of designations of origin and the introduction of substandard products (Ayan et al., 2022; Serra-Majem et al., 2020).

In the food sector, BCT seems to be a promising solution that could enable more transparency (see Javaid et al., 2021; Aldrighetti et al., 2021; Singh & Sharma, 2022; Vern et al., 2024). It is already being used to record all transactions between actors involved in the supply chain to ensure the transparency and traceability of products (see Kamilaris et al., 2019; Galvez et al., 2018). However, despite its potential, a fundamental factor is the understanding of the benefits attributed by consumers, as emphasised by Feng and colleagues (2020). Indeed, the widespread adoption of this technology depends on consumer perception and acceptance (Albertsen et al., 2020). As Singh et al. (2023) argue, the success of any technological innovation in the food sector is inextricably linked to consumer acceptance. In the consumer market, there is a growing willingness among consumers to adopt innovative technologies that facilitate access to comprehensive data on supply chain operations (Cozzio et al., 2023). In line with this premise, a study by Osei et al. (2021) hypothesises that consumers will adopt BCT technology if it can demonstrably improve food safety and quality.

Numerous studies have shown that BCTs have a positive impact on consumer purchasing decisions (Sander et al., 2018; Violino et al., 2019; Polenzani et al., 2020; Lin et al., 2022). However, other authors have pointed to a discrepancy between consumer perception and the actual value attributed to technology-specific information confirming that food has been traced with BCTs

(Shew et al., 2022). Liu et al. (2023) investigated the relationship between consumer trust in the agri-food system and certification and showed a positive influence of high levels of trust on preferences for products with traceability and the use of BCTs. The influence of BCTs on purchasing decisions, especially for certified food has a significant impact on demand and thus contributes to the success of BCT-based systems. The comprehensive traceability information that this technology provides along the entire food supply chain represents significant added value for consumers.

Contini et al. (2023) have shown that BCT promotes a positive attitude towards consumer preferences and perceptions, thus increasing trust in the system due to satisfaction with the perceived quality of the certified products. As Mazzù et al. (2021) note, BCT-based traceability also requires the involvement of certification and regulatory bodies in the supply chain system. This helps to increase consumer confidence in the reliability of the information provided, while facilitating access to comprehensive food information, including declarations from food supply chain actors, such as organic certification, chemicals used and agricultural practises. Although the technological potential of BCT has been demonstrated in previous studies (Kamilaris et al., 2019; Galvez et al., 2018), there is still little research on consumer perceptions and intentions. In particular, there is a need to investigate how consumers evaluate BCT-enabled traceability in combination with established constructs such as trust, attitudes and perceived ease of use. In recent literature, theoretical frameworks such as the Theory of Planned Behaviour (TPB) have been used to analyse consumer intentions to adopt blockchain in food systems. The studies by Dionysis et al. (2022) and Lin et al. (2021), for example, highlighted the importance of subjective norms and perceived behavioural control. However, the results regarding attitudes towards BCT were inconclusive. Contini et al. (2023) emphasised the potential of BCT to increase trust, but their results show a discrepancy between consumer trust in traditional certifications and the added value of blockchain traceability.

To fill this gap, this study investigates which factors influence consumers' intention to buy organic pasta with blockchain-based traceability.

We conducted an online questionnaire with a sample of 190 Italian respondents to investigate their behaviour towards organic pasta, as it already plays an important role in several practical applications of BCT. Using the extended TPB model, we were able to identify the factors that influence consumption. Constructs such as attitude, subjective norms and perceived behavioural control were complemented by trust in quality certifications and attitudes towards technology to increase the predictive power of the model. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyse the relationships between the constructs and validate the research hypotheses.

2. THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES DEVELOPMENT

The Theory of Planned Behaviour (TPB) is a theoretical model from the field of psychology with particular significance for predicting and changing human behaviour, especially in connection with the use of technology (Ajzen, 2020; Fleiß et al., 2024; Cudjoe et al., 2023). The TPB postulated by Ajzen (1980) is based on the assumption that individual behaviour depends on three basic elements: the individual's attitude, subjective norms or social pressure and perceived behavioural control. The TPB has been used in the consumer decision-making literature in a variety of contexts (Lin, 2007), including in the context of food choice, where it has been used to identify the motivational factors underlying the choice of one product over another (Nardi et al., 2019; Sogari et al., 2024) and to predict consumers' behaviour and intentions towards organic products (Armitage and Conner, 2001). The TPB is based on the idea that a person's behaviour depends on their intention to perform that behaviour. Behavioural intention is the result of the interaction of three factors:

1) Attitude (ATT): represents a person's inclination to perform a certain action. It is a person's opinion or judgement about adopting or performing a particular behaviour based on their values, beliefs and previous experiences with that behaviour. A positive attitude leads to a greater likelihood of behaving consistently with one's intention.
2) Subjective norms (SN): refers to the influence of other people's thoughts and attitudes towards a particular behaviour. In other words, it is the social pressure to perform or avoid a certain action, which may result from the expectations, encouragement or opinions of others.
3) Perceived Behavioural Control (PBC): refers to the perception of a person's ability to perform an action or the perception of the difficulty or ease of a particular behaviour depending on certain factors.

Several studies have investigated consumers' intention to buy products tracked with a blockchain-based system. In the study by Dionysis et al. (2022), the factors influencing the purchase intentions of coffee consumers considering coffee products that can be tracked with a blockchain-based tracking system are analysed using the TPB model. The original TPB model was extended to include additional constructs such as trust, past habits and environmental protection. The study contributes to the literature by providing insights into the factors that influence consumers' purchase intentions and shows that attitude towards coffee that is traceable with a blockchain-based traceability system, subjective norm and perceived behavioural control are positively associated with purchase intention. The study by Lin et al. (2021) also utilised the TPB to investigate the factors influencing Chinese consumers' intentions towards blockchain food traceability technology to ensure the food safety and quality of Chinese organic food. The study proposed an integrated conceptual framework combining two established theoretical models: the TPB and the informational success model (ISS). The study found that attitude and perceived behavioural control significantly and positively influence intention to use blockchain adoption, while subjective norms are positively but not significantly correlated with intention to use.

The work of Menozzi et al. (2015) analyses consumer attitudes and behaviour towards traceable food to explain the intention to buy traceable food using TPB. The results show that the predictive power of the TPB model increases significantly when new variables are added: habits, trust, past behaviours and socio-demographic variables. The results show that attitudes and trust influence the purchase intention for traceable food products.

Prisco et al. (2022) present an integrated approach that combines the TAM (Technology Acceptance Model) and the TPB (Theory of Planned Behaviour) and adds as benefits the additional factors "efficiency and safety", "reduced costs" and "quality of customer service" perceived by companies adopting blockchain technology. The results show that attitude and perceived behavioural control are the most important predictors of intention to adopt blockchain, while perception of benefits is the most important predictor of attitude. In addition, subjective norms were found to have a positive effect on behavioural intention, while the effect of perceived ease of use on attitude was not significant.

In their study, Liu et al. (2023) explored the association between consumer trust in agricultural and food systems and the impact of certifications. Their results showed a positive correlation between high consumer trust and a preference for products with certificates of origin and the use of BCTs. The influence of BCTs on consumer purchasing decisions, especially for certified food, is an important factor influencing demand and thus the success of BCT-based systems. When investigating the relationship between trust in the food system and certifications, it was found that a high level of trust positively influences preferences for PDO and BCTs, while it has a less pronounced effect on preferences for organic certifications (Contini et al., 2023). The absence of a notable interaction between the degree of trust in the food system and the preference for organic certification can be attributed to the finding that such a preference does not rely on the degree of trust in the food system in general. Rather, it is determined by the alignment of values among the various actors involved in the organic supply chain (Thorsøe, 2015). This trust is reinforced by consumer satisfaction with the quality of the products (Ladwein and Romero, 2021) and is linked to the organic certification logo (Janssen and Hamm, 2012).

Based on the analysis of previous literature, the TPB (Ajzen, 1991) was chosen as the conceptual model for this study. However, this study aims to improve the predictive power of the TPB. In addition to the original items of the TPB, such as attitude, subjective norms and perceived behavioural control, additional constructs are introduced: trust in quality certification and attitude towards technology. Based on the above literature and theory, the following hypotheses are formulated. To avoid verbosity, the indicators in the table are presented in capital letters. See Table 1 for details.

3. DATA AND METHOD

3.1. Data collection

The data collection tool consists of an online questionnaire developed on the Qualtrics platform to explore consumer intentions regarding organic pasta tracked through an innovative traceability system. The design of the questionnaire is based on the TPB presented in the previous section. The TPB approach effectively identifies factors influencing decision-making and perceived risk, making it suitable for the focus of this study on traceable products. The questionnaire aims to capture the determinants influencing consumer preferences and behaviour by incorporating the key TPB constructs. The questionnaire was divided into several sections, each designed to collect specific information related to the objectives of the study.

1) Introduction: This section provided a general overview of the study and ensured that participants kept their responses confidential.

2) TPB constructs: This section explored participants' intentions and the key dimensions of the TPB model: attitude, subjective norms and perceived behavioural control.

– The intention construct captures the likelihood

Table 1. Hypotheses and paths

Hypotheses	Path
H1: Subjective norms positively affects the intention to purchase pasta traced with blockchain technology (SN)	SN→INT
H2: Perceived behavioral control positively affects the intention to purchase pasta traced with blockchain technology (PBC)	PBC→INT
H3: Attitude towards traceability positively affects the intention to purchase pasta traced with blockch2ain technology (ATT)	ATT→INT
H4: Trust in quality certifications positively affects the intention to purchase pasta traced with blockchain technology (TQC)	TQC→INT
H5: Attitude towards technology positively affects the intention to purchase pasta traced with blockchain technology (TEC)	TEC→INT

that consumers will consider purchasing pasta with blockchain traceability once it is available.

- The subjective norms construct measures the influence of social factors, including family, academia, media, and retail, on consumers' decision to purchase pasta with blockchain traceability.
- The construct of perceived behavioural control assesses consumers' perceptions of the ease or difficulty of accessing and using products with blockchain traceability. This includes finding such products in shops and using the relevant technology, which is critical to understanding potential barriers to adoption.
- The attitudinal construct captures consumer perceptions of the benefits associated with using blockchain technology for food traceability and focuses on aspects such as safety, transparency, authenticity and production standards.

The design of these questions was guided by previous research such as Dang & Tran (2020), Dionysis et al. (2022) and Menozzi et al. (2015) to ensure that all key variables were comprehensively addressed. A 5-point Likert scale was used, ranging from 'strongly disagree' to 'strongly agree'," so that participants could express a nuanced opinion on each statement.

3) Consumer Trust in Quality Certification: Trust in quality certification is an important factor that influences consumers' confidence in the safety and authenticity of products. This construct assesses the extent to which consumers trust the quality certification information provided by companies. This block focused on assessing trust in organic food producers and sellers, drawing on the work of Li et al. (2023).

4) Attitudes towards technology: The questions in this section were organised based on the Technology Readiness Index (TRI), a scale validated by Parasuraman (2000). This index measures consumer attitudes toward technology in four dimensions: Optimism (OPT), Innovativeness (INN), Discomfort (DIS), and Insecurity (INS). By including these dimensions, the survey was able to assess how technological readiness influences consumer acceptance of traceable systems. Respondents rated their level of agreement on a 5-point scale, which allowed for an in-depth analysis of their comfort and adaptability to new technological applications.

5) Socio-demographic questions: In the last section, demographic information such as age, gender, education level and income were collected.

The scales for the TPB constructs and the Technology Readiness Index were adopted from previous studies to ensure their validity and reliability. The use of established scales in the study ensured that the constructs measured accurately reflected the concepts they were intended to assess.

The online questionnaire was administered to a sample of Italian respondents to gain insight into the factors that influence consumer behaviour. The survey was distributed online via the most popular social networking platforms (WhatsApp, Instagram and Facebook) to maximise reach and engagement. These platforms facilitated efficient data collection across all social networks and allowed for broader geographic and demographic representation. The survey was available on social media platforms from 30 October 2023 to 28 February 2024. During this period, participants were able to complete the questionnaire at their leisure. A total of 251 responses were collected, of which 190 were completed. A widely used procedure for estimating the minimum sample size in PLS-SEMs is the "tenfold rule" (Hair et al., 2011), which assumes that the sample size should be greater than 10 times the maximum number of inner or outer model terms that point to a latent variable in the model. PLS-SEM is advantageous as it does not impose strict assumptions about data distribution and can provide reliable results even when working with limited sample sizes by maximizing explained variance and minimizing estimation bias (Russo & Stol, 2021).

A combination of a random and snowball system was used to recruit participants. This approach was chosen for its practicality, as it enabled the efficient collection of responses from easily accessible individuals and facilitated the expansion of the research area and access to larger social networks. The random sample initially enabled rapid distribution of the survey, with the ques-

Table 2. Latent variables and items in detail.

Variable	Items
Intention (INT)	1. When blockchain-traceable pasta becomes available, I intend to buy it 2. When blockchain-traceable pasta becomes available, I will look for it and consider buying it 3. When blockchain-traceable pasta is available, I am inclined to buy it
Subjective Norms (SN)	1. I would buy pasta tracked via blockchain technology because my partner, family and friends approve it 2. I would buy pasta tracked via blockchain technology because scientists are in favour 3. I would buy pasta tracked via blockchain technology because the media (TV radio, social media) is in favour 4. I would buy pasta tracked via blockchain technology because the food manufacturers and supermarkets promote it
Perceived Behavioural Control (PBC)	1. I feel able to find blockchain-tracked food products in shops easily 2. I think it is easy to use apps or online tools to verify food traceability via blockchain 3. I think it is easy for me to follow the food production chain thanks to blockchain
Attitude toward BCT (ATT)	1. With the use of blockchain, organic pasta traceability information is more secure 2. The origin of organic pasta tracked with blockchain traceability is always transparent 3. Organic pasta information with blockchain traceability is more authentic 4. Organic pasta with blockchain traceability will meet higher production standards
Trust toward Quality Certifications (TQC)	1. Companies always comply with quality certification regulations 2. Companies provide consumers with transparent information on quality certification 3. Quality-certified product information is always truthful
Attitude toward Technology (TEC)	1. I am optimistic about the innovative impact of technology 2. I feel at ease to become familiar with technology 3. I believe that the adoption of technology can generate a significant improvement in transaction and information security 4. I find innovative technology to be mentally stimulating

tionnaire accessible and fillable online and a particular focus on social media users.

3.2. Data analysis

The data analysis was conducted using the softwere Stata 18.5. Structural equation modelling (SEM) was used to examine the extended theoretical framework and test the hypotheses. SEM combines various multivariate analysis methods that facilitate the investigation of multiple interactions between several latent variables (Berki-Kiss & Menrad, 2022). It is widely used in the social sciences, especially in the field of psychology. In this study, the partial least squares (PLS) structural equation model (SEM) was utilised. PLS-SEM is a statistical tool that has gained popularity among researchers who use it to analyse empirical data and evaluate different relationships simultaneously (Hair et al., 2019). The applications of covariance-based SEM (CB-SEM) and partial least squares SEM (PLSSEM) are complementary, rather than competitive (Marcoulides & Saunders, 2006). PLS-SEM is more effective than CB-SEM for analysing complex cause-effect relationships between multiple latent variables (Sarstedt et al., 2016). In addition, PLS-SEM provides reliable results even with relatively small sample sizes compared to covariance-based SEM. Furthermore, Hair et al. (2011) suggested that PLS-SEM is the optimal approach when research aims to identify causal relationships with unidentified potential variables that influence individuals' multidimensional behaviour and intentions. The process consists of two steps. These include the structural model (inner model) and the measurement model (outer model). The structural model evaluates the development of theories and hypotheses, while the reliability and validity of the constructs are evaluated using the measurement model (Russo & Stol, 2021).

4. RESULTS

Table 3 contains the most important socio-demographic indicators. In the study sample, men (41%) and women (48%) were almost equally distributed. The largest age groups were 30-39 (33%) and 40-49 (29%), followed by those over 60 (22%). The youngest group comprised only 16% of participants. It is noteworthy that there were no people between the ages of 50 and 59.

Table 3. Socio-demographic characteristics

	Detail of respondents	Percentage (%)
Gender	Male	41
	Female	48
	Other genders	6
	Prefer not to answer	5
Age	19-29	16
	30-39	33
	40-49	29
	50-59	0
	Over 60	22
Education	Elementary school	0
	Middle school	2
	High school	14
	College degree	31
	Post-degree (master, PhD.)	53
Occupation	Enterprise and public institution	31
	Employee	46
	Not employed	7
	Unemployed	4
	Retired	5
	Student	7
Income level (Euro / month)	0 €	18
	From 0 to 10.000 €	33
	From 10.001 to 26.000€	27
	From 26.001 to 55.000€	7
	From 55.001 to 75.000€	4
	From 75.001 to 120.000€	2
	>120.000€	8

The survey participants have a high level of education: the vast majority (84%) have a university or postgraduate degree. Only a small percentage (14%) have a high school diploma, and even fewer (2%) have completed middle school. None of the respondents reported having completed primary school. Most respondents (46%) were white-collar workers, followed by those working in businesses and public institutions (31%). A smaller proportion (16%) were unemployed and only 7% were students. In terms of income, the majority of participants (60%) reported an income of between €0 and €26,000. A smaller percentage (21%) earned more than 26,001 euros. Interestingly, 18% of participants stated that they had no income.

The measurement model was assessed on the basis of convergent and discriminant validity. Convergent validity refers specifically to the extent to which the indicators of the variables accurately indicate and measure them and to which other measures of the same variables correlate appropriately (Bani-Khalid et al., 2022). To determine the convergent validity of the measurement model, we assessed the loadings of the indicators, the average variance extracted (AVE) and the composite reliability (CR) as well as Cronbach's alpha. According to the literature, the values for Cronbach's alpha and composite reliability (CR), average variance extracted (AVE) and the loadings of the indicators must be higher than 0.70, 0.70, 0.5 and 0.70, respectively (Khan et al., 2023; Lin et al., 2021; Rubel et al., 2021). Accordingly, the loadings of the indicators were examined at in the first stage. As shown in Table 4 in the final measurement model, all indicator loadings exceed the threshold of 0.70. It means that the construct explains over half of the variance of the indicator. Therefore, acceptable item reliability is provided. Moreover, Cronbach's alpha and composite reliability are typically used to evaluate internal consistency reliability (Hair et al., 2019). As Table 4 shows all composite reliability and Cronbach α values are higher than 0.70, as it suggests that the elements of the same latent variable are similar.

The total mean of the squared loadings of the items associated with the construct is represented by the Average Variance Extracted (AVE) (Russo & Stol, 2021) was used to evaluate convergent validity. The Table 4 displays that theaverage variance extracted (AVE) from each latent variable is higher than 0.5. it means that the construct explains more than half of the variance of its items. In summary, Table 4 demonstrates that the standardized loadings, Cronbach's alpha, CR, AVE are all higher than the values recommended by the literature. Therefore, convergent validity was confirmed based on the results.

Discriminant validity shows the extent to which the items represent the target construct and whether a latent variable measures a separate construct (Russo & Stol, 2021). In this study discriminant validity assessed with the Heterotrait-monotrait ratio of the correlations (HTMT). The Heterotrait-Monotrait ratio of correlations (HTMT) is defined as the average of the correlations between items measuring different constructs (heterotrait correlations) relative to the geometric mean of the average correlations for items measuring the same construct (monotrait correlations) (Hair et al., 2019). The result of Table 5 illustrates that all Heterotrait-monotrait ratio of correlations (HTMT) are below the threshold value of 0.90recommended by (Hair et al., 2019), which confirms the sufficient discriminant validity of the individual constructs. It can therefore be concluded that the measurement model fulfils the required criteria for validity and reliability (reliability as well as convergent and discriminant validity).

Table 4. Reliability and validity tests.

Latent Construct	Items	Standardized loadings	Cronbach's alpha	CR	AVE
Intention (INT)	INT1	0.898	0.834	0.901	0.753
	INT2	0.932			
	INT3	0.764			
Subjective Norms (SN)	SN1	0.873	0.869	0.910	0.717
	SN2	0.858			
	SN3	0.814			
	SN4	0.840			
Perceived Behavioural Control (PBC)	PBC1	0.783	0.814	0.890	0.731
	PBC2	0.892			
	PBC3	0.885			
Attitude toward BCT (ATT)	ATT1	0.882	0.893	0.926	0.757
	ATT2	0.841			
	ATT3	0.900			
	ATT4	0.856			
Trust toward Quality Certifications (TQC)	TQC1	0.908	0.904	0.940	0.839
	TQC2	0.929			
	TQC3	0.911			
Attitudes toward Technology (TEC)	TEC1	0.916	0.916	0.947	0.856
	TEC2	0.929			
	TEC3	0.930			

We evaluate the structural model in terms of variance explained (R2), effect size (f2), predictive relevance (Q2), path coefficient (β), and hypotheses testing. The structural model is employed for the purpose of investigating the impact of exogenous variables on endogenous variables. The results of the hypotheses developed are shown in Table 6. The adjusted R2 of 0.58 indicates that subjective norms, perceived behavioural control, and attitudes toward technology explain a substantial portion of the variance in consumers' intentions to purchase traced pasta using blockchain technology.

Effect size (f2) was calculated to measure the magnitude of the significant effects. As Cohen (1988) suggested, in the structural model, f2 values of 0.02 indicate small effects. 0.15 indicates medium effects, and 0.35 indicates large effects (Bani-Khalid et al., 2022). Table 5 shows that Subjective Norms have a medium effect size, and Perceived Behavioural Control and Attitude toward Technology have a small effect size.

In this step, the Q2 value is calculated to evaluate the PLS path model's predictive accuracy. The approach relies on the blindfolding technique that eliminates individual points from the data matrix. These omitted points are then imputed using the mean, followed by estimating the model parameters. Thus, the Q^2 does not exclusively represent out-of-sample prediction; it reflects a combination of out-of-sample predictive ability and in-sample explanatory power. The blindfold procedure predicts the missing data points for each variable using these estimated parameters as inputs. Small discrepancies between the original and predicted values result in a higher Q2 value, indicating higher prediction accuracy (Hair et al., 2019). Based on the result of Table 6, the Q2 value for the endogenous latent construct is greater than zero.

The conclusions were drawn based on p-values (see Table 6), which led to the decision to accept or reject the hypotheses taken in the study.

To answer H1: "Subjective norms positively affects the intention to purchase pasta traced with blockchain technology", the results show that SN have a statistically significant positive effect on the INT to purchase blockchain-traceable products. Therefore, the H1 is accepted. The coefficient of 0.403 indicates that social influence plays a significant role in shaping consumer behaviour.

To answer hypothesis H2 "perceived behavioural control positively affects the intention to purchase pasta traced with blockchain technology", it was also found to have a positive and significant effect on intention. However, the effect size (0.032) was smaller than that of SN. Thus, H2 is accepted.

In response to H3 "Attitude towards traceability positively affects the intention to purchase pasta traced with blockchain technology", contrary to expectations, ATT did not significantly affect intention. The very low

Table 5. Results of the discriminant validity - Heterotrait-monotrait ratio of correlations (HTMT).

	INT	SN	PBC	ATT	TQC	TEC
INT						
SN	0.782					
PBC	0.762	0.680				
ATT	0.690	0.695	0.856			
TQC	0.404	0.494	0.487	0.389		
TEC	0.730	0.563	0.798	0.772	0.270	

coefficient and the high p-value (0.969) indicate that the attitude towards blockchain-traceable products does not directly influence the purchase intention in this context. Therefore, H3 is rejected.

Hypothesis H4, "Trust in quality certifications positively affects the intention to purchase pasta traced with blockchain technology", was not supported, as indicated by the non-significant coefficient (0.006) and high p-value (0.913).

To answer H5 "Attitude towards technology positively affects the intention to purchase pasta traced with blockchain technology", TEC has a significant and positive influence on purchase intention with a coefficient of 0.306. Therefore, the H5 is accepted.

5. DISCUSSION

This study provides empirical evidence on the determinants influencing consumers' intention to purchase blockchain-enriched products, with a focus on pasta. The results highlight important factors influencing consumer behaviour and offer practical implications for marketers and policy makers seeking to promote the adoption of blockchain technology in the food industry. These include subjective norms, perceived behavioral control, and attitudes toward technology, which significantly influenced consumers' purchase intentions for blockchain-traceable organic pasta. The results confirm that technology readiness is an important determinant of consumers' willingness to purchase pasta with blockchain-based traceability. Result indicates that consumers who have a positive attitude towards technological innovation are more likely to have the intention to purchase blockchain-traceable products. This is consistent with the Technology Readiness Index (TRI), which postulates that optimism and familiarity with technology can facilitate the adoption of new technological solutions (Parasuraman, 2000). The significance of this relationship suggests that fostering a positive attitude towards the benefits of technology, such as increased transparency and safety in the food supply chain, may encourage consumers to adopt products that utilise blockchain traceability. This emphasises the importance of education and technological awareness in marketing strategies. This result is consistent with the findings of Lin et al. (2021), who also found a positive correlation between consumers' technology readiness and their willingness to purchase technology-enabled products. The positive impact of TEC suggests that individuals with an optimistic attitude towards the benefits and simplicity of technological products are more willing to accept products that incorporate blockchain for traceability. This finding emphasises the importance of technological awareness and educational initiatives. Concrete examples of educational initiatives include awareness campaigns to educate the public on how blockchain improves food traceability and safety; interactive digital tools, such as mobile apps or QR codes on packaging, that allow consumers to access transparent supply chain data; and workshops and online courses aimed at consumers and food professionals to improve understanding and trust in blockchain-based certifications.

This result provides a valuable opportunity for companies to develop marketing campaigns that emphasise the transparency, security and innovation of blockchain technology. In this way, companies can gain consumer trust and encourage adoption. For example, educating consumers about how blockchain technology guarantees authenticity and traceability could appeal to technologi-

Table 6. Result of the hypothesis testing.

Hypothesis No.	Relationship	Coefficient	*p*-Value	Decision	R^2_a	Q^2	F^2
H1	SN -> INT	0.403	0.000***	confirmed		0.439	0.216
H2	PBC -> INT	0.187	0.017**	confirmed			0.032
H3	ATT-> INT	0.003	0.969	unconfirmed	0.582		0.000
H4	TQC -> INT	0.006	0.913	unconfirmed			0.000
H5	TEC -> INT	0.306	0.000***	confirmed			0.099

Note: ** $p < 0.05$, *** $p < 0.01$.

cally people who value innovation and transparency in their food.

The study found that ATT does not have a significant impact on purchase intent. This result may be explained by the specificity of blockchain technology, where consumers may not fully understand or prioritise the benefits even if they have a positive attitude towards it. Alternatively, external factors such as lack of trust could also have a stronger influence on purchasing decisions, thus obscuring the effect of attitude. This result is in line with the findings of previous studies by Dang & Tran (2020) and Prisco et al. (2022), which found that general attitudes towards a product do not always translate into purchase behaviour, especially in contexts where consumers do not fully understand or appreciate the perceived benefits. However, this finding contradicts the results of Dionysis et al. (2022), who postulated that a positive attitude towards traceability and transparency in the food industry is a good predictor of purchase intention. The divergence in results may be attributed to contextual differences or the presence of features of blockchain technology that consumers have not yet fully understood. Even if consumers are in favour of the concept of traceability, this does not necessarily mean that they are motivated to buy pasta with blockchain traceability. This suggests a disconnect between attitudes and actions, with consumer attitudes not always translating into actual purchasing behaviour. Further research could explore how this gap can be bridged by linking blockchain traceability to more directly perceived benefits such as food safety, quality assurance and environmental sustainability.

PBC was identified as an important predictor of purchase intention, suggesting that consumers who believe they have the ability and resources to identify and utilise blockchain-traceable pasta products are significantly more likely to express a purchase intention. This result is consistent with the TPB framework, which states that consumers who feel able to find and use blockchain traceable products are more likely to have the intention to purchase them. This finding emphasises the importance of ease of access and use for technology-driven innovations such as blockchain. Improving the level of control perceived by consumers through intuitive applications and clearer information can increase the likelihood of adoption. Moreover, the finding is consistent with the results of studies by Lin et al. (2021), Dang & Tran (2020), Dionysis et al. (2022) and Prisco et al. (2022), which have shown that PBC plays a central role in influencing consumer intentions, especially in the context of new technology adoption. The significant role of PBC suggests that ease of access and use are key factors for consumers. If consumers perceive blockchain-traceable pasta as easily accessible and verifiable, they are more likely to express interest in purchasing it. Therefore, companies should prioritise the development of user-friendly and accessible blockchain-based traceability solutions. One possible solution is the development of straightforward applications or digital resources that allow consumers to effortlessly verify the traceability of products, improving their perceived control over the purchasing process. Despite the inconsistency of SN as a predictor in different studies, the results of this research context show its importance. This result is consistent with the theory of planned behaviour, which postulates that the approval and support of significant others, e.g. family, friends and social networks, can strongly influence a person's behavioural intentions (Ajzen, 1991).

This suggests that opinions, recommendations and social pressure from peers, family, media and credible authorities are critical to consumers' intention to purchase pasta with blockchain traceability. This finding contradicts the discrepancies observed in other studies, but highlights an important aspect of social influence on consumer behaviour. The importance of subjective norms in this study suggests that social acceptance and approval can be effective in driving the adoption of products with blockchain traceability. Incorporating social evidence, such as endorsements from influencers, experts, and food industry leaders, into marketing strategies could effectively generate consumer interest. In addition, the implementation of educational initiatives that spread knowledge about the benefits of blockchain technology, supported by authoritative figures such as scientists and food safety professionals, could help to reinforce societal expectations of purchasing such products.

Finally, the hypothesis that trust in quality certifications directly influences consumers' intention to buy products with blockchain traceability was not confirmed. This result indicates that trust in existing quality certifications does not necessarily lead to a higher purchase intention for blockchain-traceable products. One possible explanation for this is that while consumers trust conventional quality certifications, they do not perceive traceability via blockchain as directly linked to these traditional certifications or do not see it as an added value. The lack of significant results could also be due to a knowledge gap or a lack of perceived relevance between quality certifications and blockchain technology. This result is in line with the result reported by Contini et al. (2023). They also found that trust in traditional quality certifications is not necessarily transferable to new technological applications. This can be attributed to the fact that there is no recognisable link in consumers' minds between blockchain traceability and existing quality measures. The lack of emphasis on the role of trust suggests that consumers may not perceive blockchain technology as a natural extension of existing quality certification systems. An alternative explanation is that respondents may have a high level of trust in traditional certifications, but do not perceive the value of blockchain technology as being enhanced by them. This emphasises the need for clear communication about how blockchain can complement and enhance quality certification by providing additional layers of transparency and authenticity beyond traditional systems.

6. CONCLUSION

This study provides new insights into the factors that influence consumers' intention to buy blockchain-labelled pasta. The study highlights that while attitudes towards the technology positively influence consumer purchase intentions, general attitudes towards products with blockchain traceability and trust in existing quality certifications were not found to be significant predictors. This suggests that successful marketing strategies should focus on educating consumers about the benefits of blockchain, simplifying the user experience, and leveraging social influences to drive adoption of blockchain-based traceability.

These findings have important implications for both policy makers and producers in the agri-food sector. For policy makers, the study suggests that blockchain technology can be an important tool to combat food fraud and ensure food safety and quality. There is therefore a need for supportive policies and regulations that promote the adoption and implementation of blockchain throughout the food supply chain. Governments can incentivize blockchain adoption to improve trust in food certifications through targeted policies and financial support. First, governments could launch consumer education initiatives, such as awareness campaigns and digital tools, to improve public understanding of how blockchain enhances food safety and authenticity. Finally, regulators could develop clear and enforceable standards for blockchain traceability, ensuring that certified products meet high standards of transparency and accountability.

For producers, the results of this study can help develop effective marketing and communication strategies to promote products with blockchain traceability. By emphasising benefits such as authenticity, traceability and sustainability, producers can gain consumer trust and increase the appeal of products with blockchain traceability.

While blockchain can potentially increase trust in existing quality signals, the challenge is to effectively communicate its benefits to consumers. By recognising the importance of social norms, attitudes towards technology and perceived behavioural control, stakeholders can promote transparency, accountability and sustainability in the agri-food industry, creating a more efficient and competitive environment.

Although we acknowledge the limitation of our sample size, the use of PLS-SEM ensures the robustness of our results, as this method is suitable for studies with relatively small samples (Hair et al., 2011; Sarstedt et al., 2016). This method allows us to work with small sample sizes, maximize explained variance, and minimize estimation bias (Russo & Stol, 2002). Moreover, the combination of snowball and random sampling is effective for data collection, it is important to recognise the inherent limitations of these techniques. First and foremost, there is the possibility of selection bias in non-probability sampling. For future studies, it would be beneficial to consider the use of random sampling to minimise bias.

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Agriculture 4.0: Technological adoption, drivers, benefits and challenges in Italy. A descriptive survey

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Abstract. This study aims to examine the current state of awareness regarding Agriculture 4.0 (A4.0) among Italian agricultural enterprises and to analyse variations in adoption levels, expressed needs, perceived benefits, challenges and barriers to digitalisation. Drawing on data from a descriptive survey conducted among Italian farms in 2024, this study presents findings from 1,248 respondents. The results indicate varying levels of adoption of A4.0 solutions, with monitoring systems and connected vehicles being the most widely implemented. The primary drivers for A4.0 adoption include farm management, operational control, and the enhancement of production efficiency, all of which are associated with significant perceived benefits. However, challenges such as limited interoperability and skill shortages hinder A4.0 implementation, while financial and structural constraints remain major barriers for farms seeking to transition to A4.0. This study offers valuable insights to inform policymakers, industry stakeholders, and researchers in fostering a more effective and inclusive digital transformation in the Italian agricultural sector.

Keywords: Agriculture 4.0, smart farming, digital agriculture, survey.

1. INTRODUCTION

Agriculture 4.0, also known as "digital agriculture", "smart farming" or "smart agriculture", is defined as the integration of advanced digital technologies – such as the Internet of Things (IoT), robotics, Artificial Intelligence (AI), and Big Data analytics - into the agricultural sector (Fragomeli et al., 2024). This concept is grounded in the broader framework of Industry 4.0, which is responsible for the transformation of manufacturing processes (Da Silveira et al., 2021). Agriculture 4.0 (hereby A4.0) represents a significant departure from both traditional and precision agriculture by leveraging automated, interconnected, and data-driven systems (Sharma et al., 2022).

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The transition to digitalised agricultural systems is increasingly considered as pivotal for addressing the global challenges facing society today. Rapid population growth, urbanization, industrialization, loss of arable land, freshwater scarcity, and environmental degradation have escalated concerns regarding food security (Abbasi et al., 2022). To meet the rising global demand for food, agricultural practitioners must enhance productivity while minimising pressure on natural resources such as water, land, and energy (Sharma et al., 2022).

This highlights the urgent need for efficient, data-driven agricultural practices that optimise resource usage and improve productivity (Fragomeli et al., 2024). Moreover, agriculture is both a major contributor to greenhouse gas emissions and a sector vulnerable to the impacts of climate change (Sott et al., 2020). Integrating digital technologies offers the potential to mitigate the environmental footprint of agricultural practices while bolstering farmers' resilience to climate change (Balasundram et al., 2023).

Technologies such as robotics, smart irrigation and IoT sensors can promote more sustainable agricultural practices by reducing emissions, optimising resource use, and enabling real-time monitoring of crop conditions (Assimakopoulos et al., 2024). The environmental benefits of A4.0 are closely tied to economic advantages, as digital solutions improve operational productivity, reduce resource waste, and generate cost savings (Zul Azlan et al., 2024). Additionally, from a social perspective, the digitalisation of agriculture empowers farmers by providing better decision-making tools and improving working conditions (Zhai et al., 2020).

According to Papadopoulos et al. (2024), for instance, recording and mapping technologies, combined with guidance and controlled traffic farming technologies, could lead to reductions of up to 80% in fertiliser use. Furthermore, VRT (Variable Rate Technologies) could achieve a 60% decrease in fertiliser consumption and an 80% reduction in pesticide use, while also potentially boosting yields by 62%. Additionally, robotic systems and smart machines could reduce labour by 97% and diesel consumption by 50%.

Thus, A4.0 represents a transformative approach that addresses environmental, economic, and social challenges, contributing to the development of more sustainable and resilient agricultural systems (Maffezzoli et al., 2022b).

Despite the promising role that A4.0 solutions could play in mitigating sustainability challenges while improving productivity, their uptake remains limited and fragmented (Osrof et al., 2023). Literature relates the uneven adoption rate to different factors.

Recent empirical contributions confirm that farmers' intentions to adopt new solutions go beyond purely economic considerations and are shaped by a combination of personal attitudes and perceived obstacles. For instance, Giampietri et al. (2020) emphasize the role of farmers' trust, experience and knowledge in the adoption of risk management practices, highlighting the importance of transparency about costs and benefits in adoption incentivization. Menozzi et al. (2015) highlight the relevance of farmers' attitudes and perceived control in adopting sustainable farming practices, stressing the need for better communication and collaboration within the agricultural supply chain to increase A4.0 adoption.

Meanwhile, data from farm-level surveys show how age, gender, education and farm size remain significant influencing factors for choices regarding, for example, climate change adaptation strategies (Onyenekwe et al., 2023).

Despite the ongoing discussions in the literature regarding the factors that favour or hinder the spread of A4.0, the influence of specific contexts, as countries and types of farms and farmers, remains a compelling area of investigation (Fragomeli et al., 2024; Da Silveira et al., 2023). Therefore, the authors emphasise the need for a country-specific investigation on: i) farmers' awareness of A4.0; ii) the main challenges and barriers in the adoption as well as iii) the sustainability benefits perceived. We believe that building a comprehensive knowledge around the gap between A4.0 technologies, their promised technical advantages and the actual implementation along with the feasibility of realising the related sustainability benefits, is fundamental to inform key decision makers (e.g., policy makers). This knowledge can help in shaping proper strategies which place farmers and their context-specific needs at the centre.

To this end, a survey was conducted targeting Italian farms to assess the current level of digitalisation in the agricultural sector, with a specific focus on the key dimensions influencing the adoption and implementation of A4.0 solutions. The following research questions were formulated to explore the state-of-the-art of A4.0 in Italy:

- RQ1: What is the level of adoption and awareness of A4.0 solutions in Italy?
- RQ2: What are the primary factors driving agricultural enterprises to adopt A4.0 solutions?
- RQ3: To what extent have the achieved benefits aligned with the expressed needs?
- RQ4: What are the most significant hindering factors to farmers' adoption of A4.0 solutions?

This study reveals that, while A4.0 awareness is high, adoption is uneven, with greater uptake of A4.0 solutions such as monitoring systems and connected vehicles. Adoption is mainly driven by improvements in farm management rather than operational efficiency.

Benefits generally meet or exceed expectations, particularly in optimizing technical inputs and water use, which yield both economic and environmental gains. Social sustainability effects remain debated, with some evidence of labor market benefits, though concerns persist over potential job displacement.

Despite the benefits, adoption is hindered by challenges such as interoperability, lack of skills, uncertain return on investments and limited technical support. Financial and structural barriers - especially for small farms - and poor connectivity in remote areas further constrain A4.0 uptake. This study recommends targeted policy support, training, and agrifood supply chains stakeholder collaboration to overcome these barriers and accelerate digital transformation in Italian agriculture.

The remainder of the paper outlines as follows: the first section develops a review of the existing literature on main A4.0 solutions and applications along with the factors connected to their spread, section 2 presents a literature review covering the evolution of technologies in agriculture, the main driving technologies and their applications, challenges and benefits. Section 3 explains the methodology adopted, while results are described in section 4. Finally, sections 5 and 6 discuss the main results and draw conclusions from the authors' work.

2. LITERATURE REVIEW

2.1. The evolution of agricultural technologies

Over the years, agriculture has evolved through distinct technological phases, progressing from Agriculture 1.0 to Agriculture 4.0 (Zhai et al., 2020). Traditional agriculture, Agriculture 1.0, relied heavily on manual labour and animal power. The transition to Agriculture 2.0 began in the 19th century with the introduction of mechanised farming and steam engines, which significantly increased the efficiency of agricultural activities. This second phase was also characterised by an extensive use of chemical fertilizers and pesticides, leading to environmental degradation and resource overexploitation. In the 20th century, Agriculture 3.0 emerged, leveraging advancements in computing and electronics to automate processes and enhance precision, also reducing dependency on chemicals. Today, A4.0 marks the era of smart farming, integrating digital technologies to create highly interconnected and data-driven agricultural systems (Fragomeli et al., 2024).

These innovations enable farmers to make real-time, data-informed decisions, improving productivity, sustainability, and resource efficiency while minimising environmental impact. Several terms are used to denote A4.0, such as "digital agriculture", "smart farming" and "smart agriculture" (Albiero et al., 2020).

As outlined by Sponchioni et al. (2019) and Maffezzoli et al. (2022b), Agriculture 4.0 can be defined as the evolution of precision farming, realised through the automated collection, integration, and analysis of data from the field, equipment sensors, and other third-party sources. While precision farming serves as a management system that aims at optimising crop production inputs at the field level (Bongiovanni and Lowenberg-Deboer, 2004; Pierce and Nowak, 1999; Gebbers and Adamchuk, 2010), A4.0, facilitated by the smart and digital technologies inherent in Industry 4.0, transforms previously isolated data silos into actionable knowledge, supporting farmers in decision-making both within their enterprises and across the broader agrifood supply chain. This shift from traditional to digital systems ultimately aims to enhance cost efficiency and profitability, fostering the transition to more sustainable agricultural systems from an economic, environmental and social perspective.

Recent advancements in A4.0 are marked by emerging trends that are shaping the future of farming, with a particular focus on enhancing efficiency, sustainability, and resilience. A key forthcoming development is the transition toward Agriculture 5.0, which extends the foundations of A4.0 by incorporating human-centric, sustainable, and resilient principles derived from Industry 5.0 (Abbasi et al., 2022). This shift refines the collaboration between humans and machines, aiming to improve efficiency while reducing environmental impact through circular economy strategies (Fragomeli et al., 2024). Alongside this evolution, digital twin technology has gained prominence as a tool for optimising agricultural operations (Peladarinos et al., 2023; Escribà-Gelonch et al., 2024), creating real-time virtual replicas of farms that enable monitoring, predictive analytics, and improved system integration (Polymeni et al., 2023). By simulating real-world agricultural processes, digital twins can support decision-making in areas such as crop growth, soil composition, and climate adaptability (Peladarinos et al., 2023). At the same time, the increasing challenges posed by climate change have accelerated the adoption of climate-smart agricultural (CSA) practices, which focus on building resilience against environmental concerns, reducing greenhouse gas emissions, and ensuring long-term food security through adaptive resource management (Balasundram et al., 2023).

2.2. Key technologies and applications

There are various ways to categorize the key technologies driving A4.0, as different literature studies highlight several aspects of innovation in the field. Internet of Things (IoT) enables the connection of agricultural devices and machinery, allowing real-time monitoring and automation of farm operations (Assimakopoulos et al., 2024; Abbasi et al., 2022). Sensors and wireless sensor networks collect critical data on soil conditions, weather, and crop health, supporting precision farming (Ahmed et al., 2024). Artificial Intelligence (AI) and Machine Learning process large datasets to optimise resource use, detect plant diseases, and predict yields, making farming more data-driven and efficient (Ahmed et al., 2024; Balyan et al., 2024). AI-driven systems are increasingly capable of autonomous decision-making, on-farm reinforcement learning, and real-time adaptation, significantly transforming how decisions are made at the farm level (Khanna et al., 2024). Robotics and automation include autonomous machines and drones that assist in tasks such as planting, harvesting, and spraying, reducing labour dependency and increasing precision (Ahmed et al., 2024; Balyan et al., 2024). Data analytics and Big Data play a crucial role in processing vast amounts of information collected from farms, offering insights for better decision-making (Abbasi et al., 2022). Cloud and edge computing ensure that agricultural data is processed efficiently and securely, reducing latency and enabling real-time responses in smart farming systems (Abbasi et al., 2022). Blockchain technology enhances transparency and traceability in the agricultural supply chain by securely recording transactions and ensuring data integrity (Ahmed et al., 2024).

While the technologies discussed above form the foundations of A4.0, they are not typically deployed in isolation. Instead, they are combined into integrated digital solutions, translating technological capabilities into practical tools for farming and therefore addressing different agricultural needs. Such integrated solutions include Decision Support Systems (DSS) (Araujo et al., 2021), monitoring systems (Dayıoğlu and Turker, 2021), mapping solutions (Karunathilake et al., 2023), Variable Rate Technologies (VRT) (Dayıoğlu and Turker, 2021), connected vehicles (Karunathilake et al., 2023), telemetry systems (Papadopoulos et al., 2024), robotics and drones (Araujo et al., 2021). These solutions are further described in the methodology section, where their identification, based on a review of scientific and grey literature, forms a key step of the survey design. Investigating adoption at the solution level, rather than at the level of individual technologies, better reflects how farmers actually implement digital tools in practice.

As with key technologies and solutions, the applications of A4.0 have been categorised in different ways, reflecting the broad range of domains in which digital technologies can support agricultural practices. Water and irrigation management involves smart irrigation systems, IoT-based sensors, and climate monitoring tools to optimise water use, ensuring efficient irrigation and drought adaptation (Ahmed et al., 2024; Javaid et al., 2022). Soil and crop health monitoring utilizes remote sensing, drones, and AI-driven diagnostics to assess soil fertility, detect diseases, and manage agrochemical and fertilizer use with precision (Yousaf et al., 2023). Predictive analytics for climate adaptation and yield forecasting apply Machine Learning and Big Data analytics to anticipate weather patterns, pest outbreaks, and crop productivity, helping farmers make data-driven decisions to mitigate risks (Kumar Kasera et al., 2024). Autonomous machinery and robotics enhance efficiency by using automated tractors, drones, and harvesting robots to perform tasks such as soil preparation, planting, and harvesting with minimal human intervention (Oliveira et al., 2021). Controlled-environment agriculture includes greenhouse cultivation, hydroponics, and aquaponics, which optimise growing conditions and reduce dependency on natural weather cycles, ensuring year-round food production (Maffezzoli et al., 2022b). Livestock monitoring and regulation employs wearable sensors, automated feeding systems, and AI-based health tracking to improve animal welfare, optimise breeding, and prevent diseases (Ahmed et al., 2024). Finally, supply chain optimisation focuses on product tracking, storage management, and food processing, incorporating blockchain and automation to enhance traceability, reduce waste, and streamline logistics from farm to consumer (Kumar Kasera et al., 2024).

To summarise, these technological solutions, applied in a diverse range of domains, can result in a set of improvements for farmers. Such improvements, later investigated through a survey, encompass different dimensions. A4.0 solutions can support farmers with improved forecasting capabilities and improved farm management and control; support planning and scheduling activities, while also facilitating and streamlining workforce processes; optimise the use of technical inputs (water, pesticides, fertilizers), enhance efficiency and reduce losses due to pests and diseases. Finally, through monitoring and measurement, they enable increased awareness on farm operations and improve the quality of agricultural products.

All these enhancements can lead to substantial economic, environmental and social benefits.

2.3.Sustainability benefits

A4.0 yields significant economic, social, and environmental benefits, thereby fostering a profound transformation of the agricultural sector. Economically, it enhances resource use efficiency by optimising the application of water, fertilizers, and pesticides, reducing waste, and increasing agricultural yields. This leads to greater profitability for farmers and more cost-effective farming practices (Zul Azlan et al., 2023; Abbasi et al., 2022). Additionally, the automation and digitalisation of farm operations, such as harvesting, sowing, and irrigation, result in time and cost savings, improving operational efficiency (Pradel et al., 2022). The introduction of predictive models and real-time data analysis can help farmers forecast adverse conditions like disease outbreaks or extreme weather, thereby improving the resilience of agricultural systems and ensuring production even in challenging circumstances (Zul Azlan et al., 2023). From an environmental standpoint, smart farming practices significantly reduce agriculture's ecological footprint. Precision agriculture technologies, AI-driven crop monitoring, and automated machinery facilitate the efficient use of resources, leading to reduced fuel consumption, lower greenhouse gas emissions, and improved water conservation (Cambra Baseca et al., 2019). Moreover, the deployment of technologies such as drones and IoT-based environmental monitoring systems supports soil health management, optimises nutrient use efficiency, and strengthens climate resilience (Abbasi et al., 2022). By minimising waste and promoting environmentally responsible practices, A4.0 emerges as a key driver of sustainable agricultural development (Zul Azlan et al., 2023).

From a social perspective, A4.0 plays a crucial role in enhancing the well-being of rural communities, agricultural workers, and consumers. By promoting more efficient and sustainable farming practices, A4.0 strengthens food security, mitigates food shortages, and reduces waste (Jin et al., 2020). Furthermore, the integration of advanced technologies equips farmers with improved decision-making tools, contributing to higher living standards by lowering labour costs and enhancing working conditions (Da Silveira et al., 2021). Additionally, A4.0 enhances product quality and traceability, ensuring food safety and addressing consumer concerns (Zul Azlan et al., 2023). The integration of advanced digital monitoring technologies can in fact support the verification of environmental and social standards along the food supply chain (Meemken et al., 2024). These systems not only strengthen sustainability management but also offer new avenues for accountability and trust in food systems. However, they further raise important questions about equity and data access, which merit further attention as digital monitoring expands (Meemken et al., 2024). Despite such promising social benefits, scholars have also drawn attention to the danger of overly optimist narratives that see these innovations as universal solutions. Klerkx et al. (2020) emphasize the need to account for the social and ethical implications of A4.0 transitions, particularly in terms of labor displacement, rural depopulation, power concentration, and the marginalization of alternative, potentially more accessible technologies.

In fact, while A4.0 promises numerous benefits, its impacts are not unilaterally positive. Muhl et al. (2022) stress how digital agriculture may reinforce existing inequalities and that social issues like food insecurity, often driven by broader social injustices, will not be solved by technological development alone. The sustainability debate thus calls for an inclusive and responsible approach to the use and development of these technologies, ensuring accessibility across different contexts (Muhl et al., 2022).

2.4. Challenges and barriers

The adoption of A4.0 technologies is hindered by a range of significant challenges and barriers, as highlighted by (Assimakopoulos et al., 2024, Da Silveira et al., 2021; Da Silveira et al., 2023; Fragomeli et al., 2024). An interesting classification of challenges is provided by Lezoche et al. (2020), where a distinction is made between organizational, social and technological challenges. Among organization challenges, one of the most frequently associated with A4.0 adoption is the high cost connected to the technology adoption, including the initial investment required for the implementation of the components, the ongoing maintenance costs, and the cost of skilled labour (Da Silveira et al., 2023). These financial challenges are particularly burdensome for small-scale farms, which often lack the necessary capital or access to financing options to invest in such innovations (Assimakopoulos et al., 2024). Additionally, from a more social perspective, the complexity of modern agricultural technologies and the advanced skills required for their operation present further obstacles (Fragomeli et al., 2024). These barriers are not unique to the Italian context; similar challenges have been widely observed in other regions, particularly among smallholder farmers. For instance, Mhlanga et al. (2023) highlight the digital transformation obstacles in African agriculture, where factors such as limited infrastructure, insufficient digital literacy, lack of funding mechanisms, and farmer resistance significantly constrain adoption. In general, farmers with limited technological proficiency - especially older individuals or those with lower levels of formal education - may struggle to integrate digital tools into their daily operations (Assimakopoulos et al., 2024). It can be stated that, beyond costs, adoption is shaped by a complex interaction of operator characteristics (such as age, education, and digital skills), farm-level attributes (including size, income, and specialization), and the perceived attributes of the technologies themselves – such as their trialability, ease of integration, and perceived utility (Khanna et al., 2024).

From an organizational perspective, uncertain regulatory aspects and complex legal frameworks often hinder adoption (Lezoche et al., 2020), highlighting the role of manufacturers and governmental bodies as critical in mitigating these challenges.

Looking at technological challenges, a further barrier is often recognized in inadequate infrastructures, particularly in rural areas, where poor internet connectivity and restricted access to technical support networks hinder the full utilization of digital technologies (Da Silveira et al., 2023; Fragomeli et al., 2024). Moreover, farmers already managing extensive daily responsibilities may perceive these new technologies as overly time-consuming or complex, together with concerns about lack of interoperability and issues about data security and privacy (Lezoche et al., 2020). Moreover, many farmers report a lack of accessible training programs, technical guidance, and support services, which prevents them from fully understanding and implementing digital tools (Da Silveira et al., 2023).

These financial, educational, infrastructural, and institutional barriers underscore the multifaceted challenges associated with adopting A4.0 technologies. Addressing these issues through targeted policies, improved infrastructure, and comprehensive training initiatives is essential for promoting widespread and equitable adoption of digital farming solutions.

3. RESEARCH METHODOLOGY

The primary objective of this research is to assess the current state of digitalisation within the Italian agricultural sector, with a specific focus on different key dimensions that shape the adoption and implementation of A4.0 technologies. To evaluate the state-of-the-art of A4.0 in Italy, the following research questions have been formulated:

- RQ1: What is the level of adoption and awareness of A4.0 solutions in Italy?
- RQ2: What are the primary factors driving agricultural enterprises to adopt A4.0 solutions?
- RQ3: To what extent have the achieved benefits aligned with the expressed needs?
- RQ4: What are the most significant hindering factors to farmers' adoption of A4.0 solutions?

To address these research questions, the study examines the following dimensions:

Adoption and awareness of A4.0 solutions: assessing the extent to which identified A4.0 solutions have been implemented across the sector and the level of awareness that Italian farms have regarding these technologies.

Drivers of digitalisation: identifying the factors motivating farms to explore and implement the proposed A4.0 solutions, highlighting key needs and expectations.

Benefits achieved: evaluating the advantages achieved through the adoption of A4.0 solutions with regards to the specific needs expressed.

Challenges encountered by farmers adopting A4.0 technologies: examining obstacles that farms encountered during the adoption and implementation process of A4.0 solutions.

Inhibiting factors for non-adopting farmers: investigating the underlying reasons for the hesitation or inability of non-user farmers to adopt A4.0 solutions.

The last two categories are drawn from the literature on "challenges and barriers", which typically does not distinguish between adopters and non-adopters. However, based on the authors' experience and discussions with farmers and technology providers, this distinction was deemed necessary to better reflect the obstacles faced by Italian agricultural enterprises in uptaking and using A4.0 solutions.

To address these objectives systematically, the research followed a structured methodology comprising the following steps:

Sample development. The research referenced data from the 7th General Census of Agriculture of the Italian National Institute of Statistics (ISTAT)[1] to identify a representative sample of Italian agricultural enterprises. The sampling framework accounted for critical variables, including farm size, production type, and geographic distribution, ensuring a diverse and comprehensive representation of the Italian agricultural sector. The sample was drawn from three perspectives: (1) geographic distribution: Italian farms were grouped in four main regions to capture macro-regional variations in farms geographical distribution (Table 1). (2) Primary crop production: Italian farms have been classified based on their primary agricultural products, determined by the proportion of Utilised Agricultural Area (UAA) allocated to specific cultivations (Table 2). (3) Farm size: Italian farms have been categorised according to their UAA size, allowing for an analysis of adoption patterns by operational scale (Table 3). A proportionate stratified random sampling approach was employed, whereby the

[1] https://www.istat.it/statistiche-per-temi/censimenti/agricoltura/7-censimento-generale/

total population, as defined by ISTAT, was divided into mutually exclusive strata. Each stratum was sampled in proportion to its representation within the overall population. Within each stratum, participants were selected using a random sampling method.

Identification of a set of A4.0 solutions. A tailored set of A4.0 solutions was developed in alignment with the operational characteristics of the agricultural sector based on an analysis of scientific and grey literature on this topic (Araújo et al., 2021; Dayıoğlu and Turker, 2021; Karunathilake et al., 2023; Papadopoulos et al., 2024). This set comprises the following A4.0 solutions:

DSS – Decision Support Systems, that assist farmers in decision-making by optimising management and agronomic choices based on field data, environmental, weather and soil data, and information provided by the farmer. These systems can directly provide both management and agronomic advice to the users.

Monitoring systems, enabling the monitoring, often remotely and automatically, of environmental conditions or other parameters related to crops.

Mapping solutions, allowing the mapping of soil and crops, providing spatial variability in soil, crop, and hydrological characteristics, among others. These spatialised datasets can be used for various purposes such as variable rate input applications, agronomic decision-making support, and operational management.

Variable Rate Technology (VRT) solutions that enable field operations and the distribution of inputs based on the spatial variability detected in the field and the needs of the soil and crop systems.

Connected vehicles, i.e. digitally connected machinery that is equipped with integrated digital technologies, such as assisted driving, precision navigation systems, and auto-steering systems.

Telemetry systems and solutions for vehicle and equipment monitoring, that can locate, monitor and provide assisted control of agricultural machinery, including auto-steering systems and telematic solutions for fleet monitoring, predictive maintenance, and machinery efficiency improvement.

Robotics, i.e. solutions involving autonomous machinery capable of movement, decision-making, and performing specific tasks and crop operations with little or no operator intervention.

Drones, i.e. solutions and services involving the use of drones for mapping crops and land through cameras and sensors, monitoring crop health, and applying products or biological control agents.

For the purpose of this research, *Farm Management Information Systems (FMIS)* have been excluded from the analysis, as they are classified as enabling technologies rather than core components of the A4.0 paradigm. As Industry 4.0 evolves and digital technologies continue to expand and mature into practical solutions for farmers, it becomes crucial to distinguish between core components of the paradigm and enabling technologies. While enabling technologies play a vital role in supporting A4.0, they are considered complementary rather than fundamental elements of the paradigm itself.

Survey design and implementation. An online survey was developed and distributed targeting farms identified through the sampling framework. The online format was chosen for its cost-efficiency, ease of administration, and ability to minimise errors associated with manual data collection, as also reported by van Selm and Jankowski (2006) and Maffezzoli et al. (2022a).

This survey consisted of seven sections:

1. *General information*, collecting foundational and demographic details about the respondent and their agricultural enterprise.
2. *A4.0 awareness and implementation*, assessing the level of familiarity and the extent of adoption of the proposed set of A4.0 solutions.
3. *Needs, benefits, and challenges*, exploring the specific needs driving the adoption of A4.0 solutions, the benefits achieved, and the challenges encountered during their implementation.
4. *Data management capabilities*, evaluating the farms' ability to collect, store, analyse, and utilize data effectively to inform decision-making processes.
5. *Digital skills*, assessing the competences and level of expertise of farm operators in relation to A4.0 solutions.
6. *Investments*, reviewing past investments, current expenditures, and anticipated future investments in A4.0 solutions.
7. *Inhibiting factors*, identifying the barriers and constraints preventing or limiting the adoption of A4.0 solutions.

The full set of questions included in each section of the survey is provided in Appendix A, located at the end of this manuscript.

Data collection. Data collection was conducted from September 2024 to December 2024. The process yielded a total of 1,248 valid responses, providing a robust dataset for detailed analysis. Tables 1, 2 and 3 report the sample of responses collected according to the critical sampling variables and table 4 provides a summary of the main descriptive statistics on collected data.

The tables presented below highlight a discrepancy between the sample distribution and that of the overall

Table 1. Total population and sample size and their distribution across Italian regions (number of farms).

	Pop. size distr.	Pop. size distr. (%)	Sample size distr.	Sample size distr. (%)
North-west	113,972	10%	304	24%
North-east	187,429	16%	319	26%
Centre	179,230	16%	328	26%
South and Islands	652,392	58%	297	24%
Total	1,133,023	100%	1,248	100%

Table 2. Total population and sample size and their distribution across primary crop productions (UAA - Utilised Agricultural Area).

	Pop. size distr.	Pop. size distr. (%)	Sample size distr.	Sample size distr. (%)
Cereal crops	3,054,288	34%	31,923	19%
Vineyards	742,926	8%	92,693	56%
Fruit crops	444,805	5%	7,310	4%
Fodder crops	2,564,217	28%	3,469	2%
Olive cultivation	1,114,593	12%	4,723	3%
Vegetable crops	445,966	5%	4,490	3%
Legumes	85,007	1%	132	0.1%
Citrus fruits	149,863	2%	21,353	13%
Industrial plants	477,091	5%	562	0.3%
Total	9,078,756	100%	166,655	100%

Table 3. Total population and sample size and their distribution across farms' size (number of farms).

	Pop. size distr.	Pop. size distr. (%)	Sample size distr.	Sample size distr. (%)
0 hectares	12,499	1%	23	1%
Up to 0.99 hectares	228,481	20%	19	2%
From 1 to 1.99 hectares	209,662	18%	61	5%
From 2 to 2.99 hectares	128,381	11%	55	4%
From 3 to 4.99 hectares	147,320	13%	123	10%
From 5 to 9.99 hectares	160,133	14%	209	17%
From 10 to 19.99 hectares	109,545	10%	262	21%
From 20 to 29.99 hectares	45,118	4%	104	8%
From 30 to 49.99 hectares	41,167	4%	109	9%
From 50 to 99.99 hectares	32,487	3%	120	10%
From 100 onwards	18,230	2%	163	13%
Total	1,133,023	100%	1,248	100%

population, resulting in an overrepresentation of farms located in Northern Italy and an underrepresentation of those in the South and Islands. This imbalance may

Table 4. Summary of main descriptive statistics of collected data.

	Unit	Mean	Median	Std	Min	Max
Farm size	Ha	22.21	38.50	1,718.21	0	40,000
Farm annual turnover	EUR					
Less than €50,000	share	0.35				
Between €50,000 and €250,000	share	0.38				
Between €250,000 and €500,000	share	0.12				
Between €500,000 and €1,000,000	share	0.06				
Over €1,000,000	share	0.09				
Employees in farm	no.	3.69	11.75	6.60	0	950
A4.0 solutions adopted in farm	no.	2.68	4.00	1.65	0	8
Total amount spent on A4.0 solutions by farm	EUR					
Less than €5,000	share	0.23				
Between €5,000 and €15,000	share	0.17				
Between €15,000 and €30,000	share	0.13				
Between €30,000 and €50,000	share	0.09				
Between €50,000 and €75,000	share	0.08				
Between €75,000 and €100,000	share	0.07				
More than €100,000	share	0.23				

introduce a geographical bias into the analysis. Moreover, the average Utilised Agricultural Area (UAA) of the sampled farms, amounting to 22 hectares, is notably higher than the national average of 11.1 hectares reported by ISTAT[2], indicating a sample skewed toward more structured and capital-intensive farming operations. The sample also includes a disproportionately large share of vineyard farms, a sector typically associated with higher profitability and investment capacity, which may further influence the study's results.

However, these deviations do not necessarily compromise the validity of the findings. The research primarily aims to investigate the adoption and perceived benefits of A4.0 solutions, an area where more structured and technologically advanced farms are expected to play a pioneering role (Giua, 2022). Consequently, focusing

[2] https://www.istat.it/it/files/2022/06/censimento_agricoltura_gismondi.pdf

on more innovative and capitalised enterprises allows for a more detailed understanding of current trends, challenges, and potential impacts, which can serve as a reference point for the broader agricultural sector as it transitions toward digitalisation.

Prior to presenting the results of the survey data analysis, the authors provide a table outlining the key descriptive statistics of the collected dataset.

The descriptive statistics in the table above highlight that farm size distribution is skewed. This asymmetry is commonly observed across many countries, as both very large and very small farms coexist, often with significantly different spending capacities, as also noted by the OECD (Bokusheva and Kimura, 2016).

4. RESULTS

4.1. A4.0 awareness and adoption level

The initial findings of this analysis focus on the current levels of adoption of A4.0 solutions among survey respondents. A summary of these results is presented in Figure 1. To assess awareness of A4.0 solutions, a four-point scale was employed, ranging from low to high familiarity, following the approach outlined by Maffezzoli et al (2022a). This scale effectively distinguishes varying levels of awareness and facilitates cross-tabulation, allowing for the identification of patterns across different respondent groups. The four levels of awareness are defined as follows: (a) *Unknown*, representing a complete lack of familiarity, indicating no awareness of the existence of the proposed solution; (b) *Known*, denoting limited familiarity and implying that the respondent has heard of the solution, but possesses only a superficial understanding; (c) *Used in the past, not anymore*, indicating theoretical familiarity and suggesting that the respondent has a solid understanding of the solution despite no longer using it; and (d) *In use*, representing practical familiarity, meaning the respondent not only knows about the solution, but also employs it.

The data reveal varying levels of adoption and awareness of A4.0 solutions. Key findings show that approximately 26% of respondents implement *monitoring systems* and *connected vehicles*, making these among the most widely adopted A4.0 solutions. Meanwhile, 20% of respondents adopted *mapping solutions* and 19% employed *telemetry systems and solutions for vehicle and equipment monitoring*.

Adoption rates for *Decision Support Systems (DSS)* and *Variable Rate Technology (VRT) solutions* are notably lower, at 7% and 6% respectively. *Robotics* and *drones* show the lowest adoption rate, standing at only 3%, likely due to constraints related to cost, technical expertise, or perceived necessity.

Disaggregated data by farm size reveal that only 23% of farms with less than 10 hectares of UAA have adopted at least one A4.0 solution. Similarly, among farms with annual revenues below EUR 50,000, the adoption rate stands at 21%. However, adoption increases substantially with scale: 66% of farms with a UAA between 100 and 199.9 hectares have adopted A4.0 technologies, and

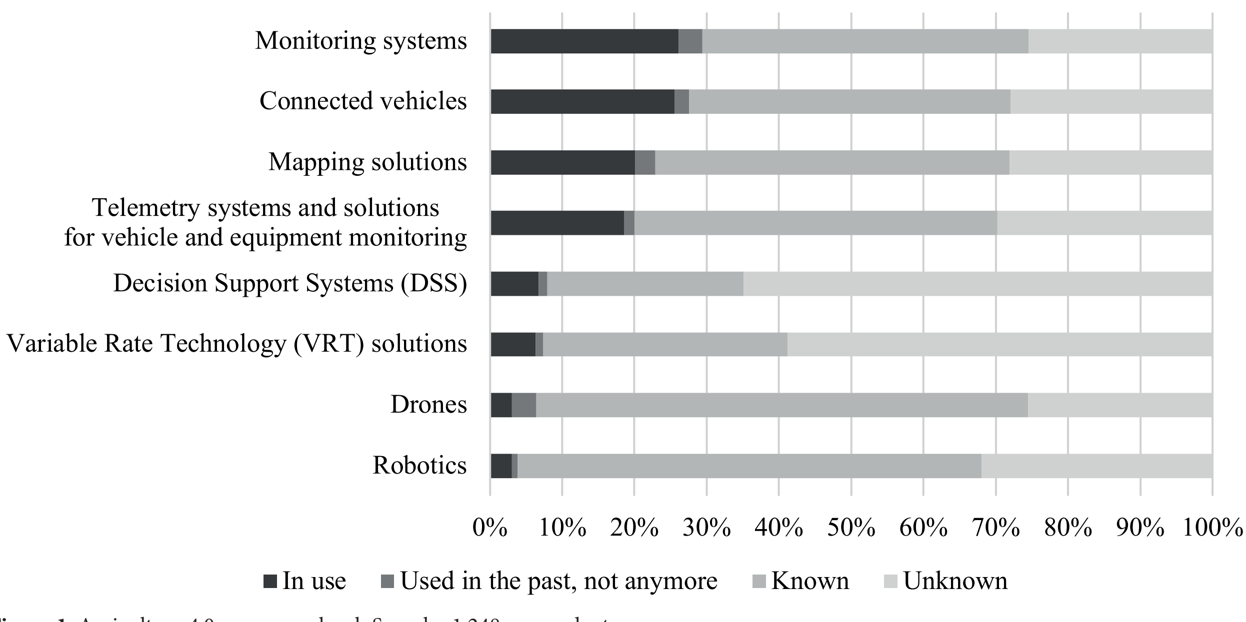

Figure 1. Agriculture 4.0 awareness level. Sample: 1,248 respondents.

this figure rises to 82% for farms exceeding 200 hectares. A comparable trend is evident with respect to economic size, where adoption reaches 74% among farms with annual revenues between EUR 500,000 and EUR 1,000,000, and rises further to 81% for those with revenues above EUR 1,000,000.

In contrast, our findings do not reveal substantial differences in A4.0 adoption based on the age or education level of farm managers. The only exception is among managers over the age of 65, who show a lower adoption rate (30%). Similarly, post-graduate degree holders are the only educational group exhibiting higher-than-average adoption rates (48%).

With regard to agricultural production types, enterprises primarily engaged in cereal cultivation report higher adoption rates of A4.0 solutions (49%), alongside vineyard and fodder farms (both at 43%). The relatively higher A4.0 adoption among cereal and fodder producers can be attributed to the extensive nature of these cropping systems, which can be particularly well-suited to the application of A4.0 solutions in optimizing operations over wide areas. Conversely, vineyard enterprises, typically characterized by higher revenue margins, tend to possess greater financial capacity to invest in innovation, thereby facilitating the uptake of digital solutions and innovative technologies.

4.2. Needs expressed and benefits perceived from A4.0 implementation

To comprehensively analyse the key drivers that motivated respondents to adopt and implement A4.0 solutions, this study focuses on the specific needs expressed by farmers. These needs reflect both strategic and operational priorities, ranging from farm management and control to the optimisation of input consumption.

Figure 2 reveals a substantial level of awareness among respondents regarding the broad and multifaceted nature of the A4.0 paradigm. Rather than being perceived merely as an extension of precision agriculture - whose primary goal is to deploy technological solutions in the field to optimise input consumption and reduce costs - A4.0 appears to be increasingly recognised as a comprehensive framework for enhancing overall farm management and control, with positive effects along the overall agrifood supply-chain. This paradigm shift suggests that farmers view A4.0 not only to refine specific agricultural practices, but also as an integral component in fostering a more efficient and data-driven agricultural enterprise.

Among the ten most frequently expressed needs related to farm management and control, the most prominent include enhancing forecasting capabilities (41%), particularly in areas such as disease outbreaks, crop requirements, plant growth and yield projections, improving control and management processes within the farm enterprise (38%) with a focus on better decision-making and operational efficiency, optimising the planning and scheduling of agricultural activities (32%) and increasing awareness of ongoing farm activities and operations (31%). Similarly, in relation to the optimisation of input consumption, respondents identified key areas where A4.0 solutions could bring significant improvements, including optimising the use of technical inputs such as fertilisers and agrochemicals (28%) and enhancing the efficiency of machinery and equipment utilisation (26%), contributing to both cost reductions and opera-

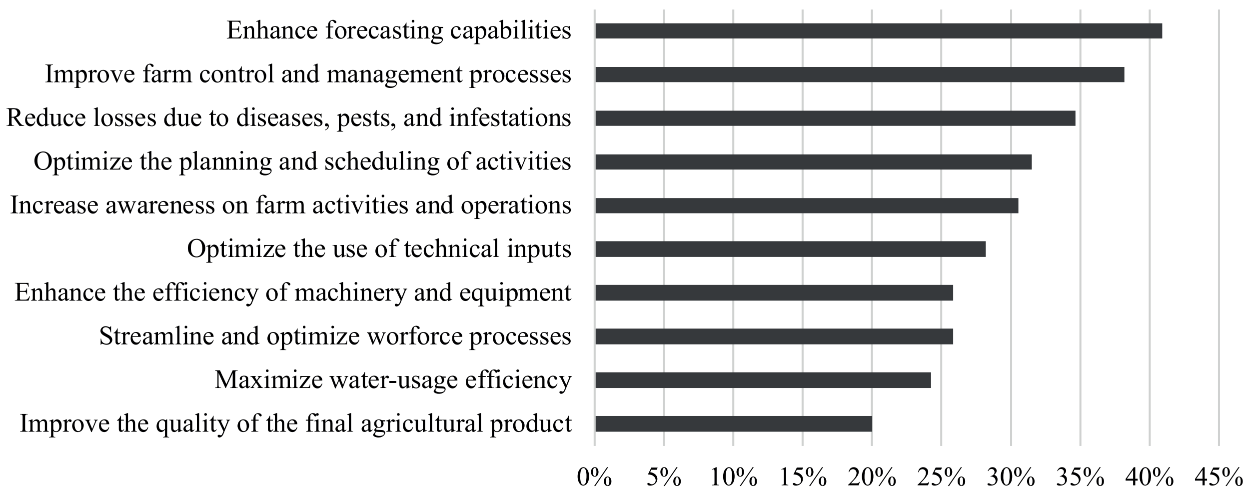

Figure 2. Needs expressed by respondents. Sample: 511 respondents who adopted at least one of the proposed Agriculture 4.0 solutions. Respondents could choose a maximum of 5 options.

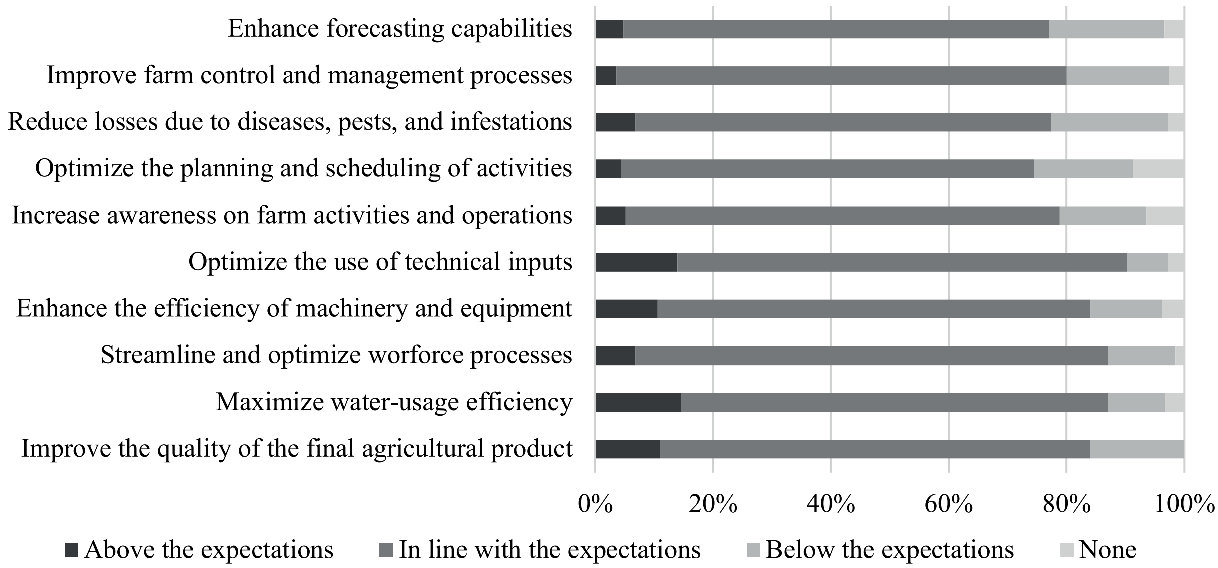

Figure 3. Benefits perceived by respondents. Sample: 511 respondents who adopted at least one of the proposed Agriculture 4.0 solutions.

tional sustainability. Furthermore, respondents expressed the need to streamline and optimise workforce processes (26%), ensuring that operators can perform tasks with efficiency and effectiveness, and to maximize water-use efficiency (24%), which is particularly critical in the context of recent meteorological events in Italy: in 2024, the country experienced heavy rainfall in the northern regions, while facing severe droughts in the south[3].

Furthermore, respondents reported adopting A4.0 solutions for additional objectives, including reducing losses due to diseases, pests, and infestations (35%), a critical aspect of maintaining both yield stability and crop health, and improving the quality of the final agricultural product (20%) to meet regulatory requirements.

Figure 3 illustrates the perceived benefits derived from the adoption of A4.0 solutions, as evaluated in relation to the specific needs previously expressed by respondents. The findings indicate that, on average, the implementation of A4.0 technologies resulted in outcomes that aligned with initial expectations for most adopters (74% on average). Additionally, a subset of respondents (8% on average) reported that the benefits they experienced exceeded their initial expectations.

These results suggest that most farmers who invested in A4.0 solutions perceived their adoption as a successful means of addressing their agricultural needs, with reported benefits generally meeting anticipated outcomes. However, a smaller proportion of respondents indicated that the benefits they obtained were either below their expectations (14% on average) or entirely absent (4% on average), highlighting potential limitations in implementation effectiveness, technology adoption challenges, or contextual constraints that may have hindered the full realisation of expected advantages.

Furthermore, the analysis reveals that the perceived benefits were more pronounced in activities related to the optimisation of input consumption compared to those associated with farm management and control. Specifically, an average of 11% of respondents reported experiencing benefits that exceeded their expectations in the domain of input consumption optimisation. In contrast, only an average of 4% of respondents indicated that benefits surpassed expectations for farm management and control activities. This suggests that A4.0 solutions may be particularly effective in enhancing input efficiency, resource utilisation, and operational streamlining, whereas their impact on broader management and control functions may be more variable or dependent on additional contextual factors.

Moreover, Italian farmers who have already adopted A4.0 solutions exhibit a significantly higher propensity to invest further in these technologies compared to non-adopters. Specifically, 20% of current users reported their intention to invest more than EUR 50,000 in A4.0 technologies within the next year, whereas only 3% of non-users indicated an equivalent investment plan. Furthermore, 27% of adopters expected to allocate between EUR 5,000 and EUR 30,000, compared to just 18% among non-adopters. Notably, 55% of non-users were

[3] Agro-meteorological Monitoring INDices (AgroMIND) map on Agricultural Drought (SPEI6) (https://wonderful-bush-09061f403.5.azurestaticapps.net/AgroMIND.html)

unable to estimate their future investments, in contrast to only 26% of current users. These findings suggest that A4.0 adopters, having already perceived benefits (often exceeding expectations) are more inclined to pursue further technological advancement and exhibit a clearer strategic orientation toward digital transformation.

4.3. A4.0 implementation challenges and factors inhibiting A4.0 adoption

This study also aims to assess the challenges encountered by respondents who have adopted at least one of the proposed A4.0 solutions, as well as the barriers faced by those who either could not or chose not to adopt any of these solutions.

Figure 4 presents the challenges encountered by farms that have implemented A4.0 solutions. The findings indicate that one of the most significant issues – reported by 36% of respondents – is limited or non-existent interoperability among the adopted solutions. Many farmers, indeed, struggle with integrating different digital tools within their existing farm management systems, leading to inefficiencies and operational difficulties (Khanna et al., 2024).

Following interoperability concerns, other notable challenges include the lack of appropriate skills to effectively utilise A4.0 solutions (30%) and the perceived inadequacy of return on investment (26%), suggesting that respondents may not see immediate or sufficient financial benefits from their A4.0 investments, potentially discouraging further technological adoption. Furthermore, 26% of respondents indicate insufficient or unreliable technical assistance, which further limits A4.0 effectiveness together with operational challenges (20%) and inadequate connectivity (16%).

Interestingly, only 6% of respondents reported that they did not face any challenges during A4.0 implementation. This finding suggests that most adopters have encountered at least some difficulties in integrating and implementing A4.0 solutions, emphasising the need for targeted interventions to enhance system compatibility, improve user experience and provide better support mechanisms for farmers transitioning to digital technologies.

Figure 5 illustrates the key barriers that have prevented farms from adopting A4.0 technologies. One of the most frequently cited limitations is farm size, with 68% of respondents indicating that their farms are too small to justify investment in A4.0 solutions. This is not surprising, as Table 3 shows that in the Italian context, most farms (77%) are small or medium-sized.

Further constraints concern the possible exploitation of A4.0 solutions, with 59% of respondents believing that they would not fully exploit these solutions and 50% stating that their current agricultural technologies and management practices adequately meet their business needs, thereby reducing the perceived necessity of implementing A4.0 solutions.

Financial concerns also play a significant role, as 45% of respondents believe that the anticipated benefits do not justify the required investment, while 41% struggle to see the potential economic advantages of incorporating digital tools into their operations. Additionally, financial constraints further limit adoption, with 38% of respondents citing their inability to spread investment costs over time and 36% highlighting the difficulty of sharing these costs across multiple enterprises. Bureaucratic challenges also emerge as a deterrent, as 36% of respondents report difficulties in accessing financial incentives due to stringent requirements and administrative burdens, while 22% point to restricted access to credit lines as a further impediment.

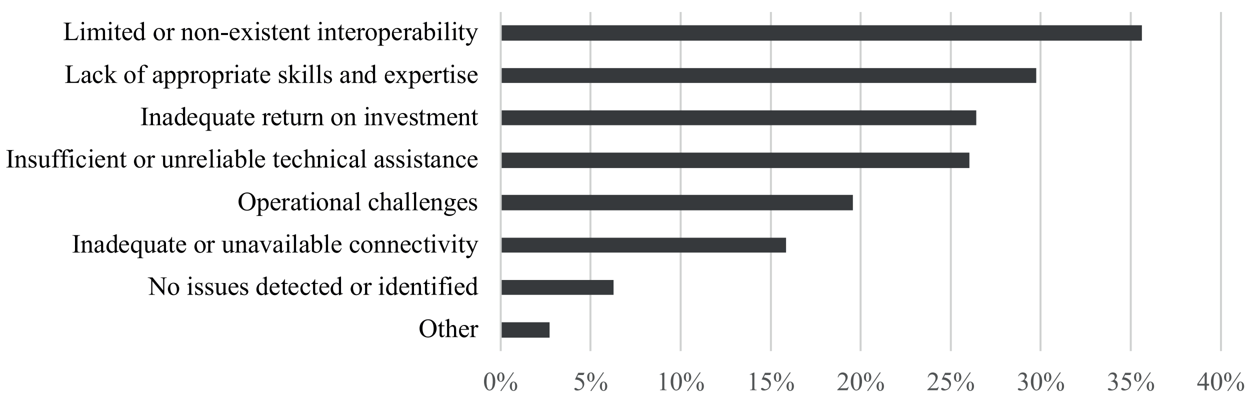

Figure 4. Challenges encountered by respondents. Sample: 511 respondents who adopted at least one of the proposed Agriculture 4.0 solutions. Respondents could choose more than one option.

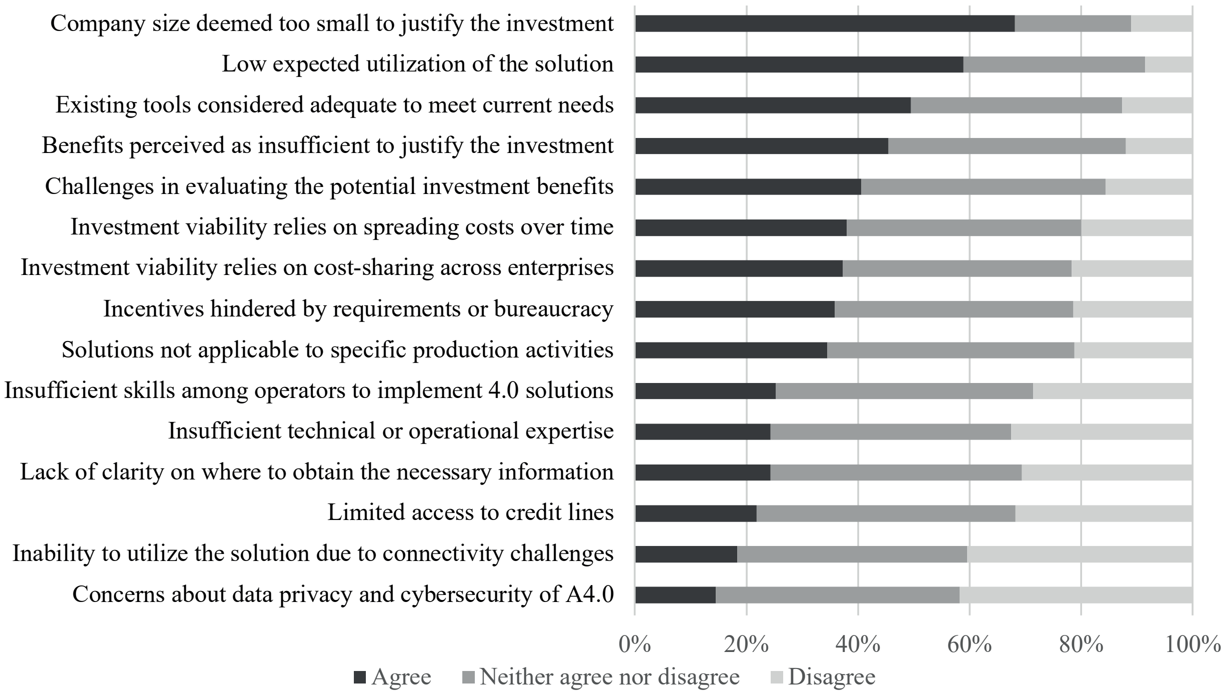

Figure 5. Inhibiting factors faced by respondents. Sample: 737 respondents who have not adopted any of the proposed Agriculture 4.0 solutions.

While digital skills were identified as a notable challenge among those who have already adopted A4.0 solutions, they appear to be a less pressing concern for non-adopters: only 25% of respondents cited a lack of necessary competencies as a barrier, while an equal proportion stated that their collaborators also lacked the required skills. Such discrepancy in how digital skills are perceived between adopters and non-adopters reflects an experience gap in A4.0 implementation: non-adopters seem to not yet acknowledge the digital skills challenge because they have not engaged with A4.0 deeply enough, whereas adopters have firsthand knowledge of the difficulties and their impact on agricultural activities. Furthermore, 24% of non-adopters indicated that they did not know where to access basic information about A4.0 solutions, underscoring the need for better dissemination of knowledge and educational resources.

Beyond financial and technical barriers, several other factors have contributed to the reluctance to adopt A4.0 technologies. A lack of applicability to specific agricultural production areas was cited by 34% of respondents, suggesting that certain farming sectors or operational models do not align with the capabilities offered by the proposed A4.0 solutions. Connectivity issues also play a role, with 18% of respondents identifying poor internet access as a constraint, particularly where digital infrastructure may be insufficient. Additionally, concerns related to data security and privacy were reported by 15% of respondents, indicating a degree of hesitation regarding the management and protection of sensitive farm data in digital systems.

These findings highlight the multifaceted nature of the barriers impeding A4.0 adoption, encompassing economic, technical, infrastructural, and informational challenges. Addressing these concerns through targeted policies, financial support mechanisms, improved access to training, and enhanced digital infrastructure could facilitate broader adoption and ensure that a wider range of farms can benefit from the efficiencies and advancements offered by A4.0 solutions.

5. DISCUSSION

This study examines the adoption and awareness levels of Agriculture 4.0 (A4.0) solutions, the drivers influencing technological adoption, the benefits obtained, as well as the challenges faced by A4.0 users and the inhibiting factors expressed by A4.0 non-adopters. A comprehensive understanding of these aspects is essential for policymakers, researchers, and industry stakeholders to identify obstacles and develop strategies aimed at facilitating the widespread integration of digital technologies in the agricultural sector. Such integration holds the potential to enhance productivity, efficiency, and sustainability within Italian agriculture.

The findings indicate that while there is widespread awareness of A4.0 solutions among Italian farmers, adoption levels vary significantly. These discrepancies are closely associated with the structural characteristics of farming enterprises, particularly the size of the Utilised Agricultural Area (UAA) and the level of annual turnover. Existing literature has consistently highlighted that the uptake of digital agricultural technologies is contingent upon several structural and socio-economic factors, including farm scale, crop specialization, farmer age, and educational background (Giua, 2022). At the national level, our results corroborate this evidence, demonstrating that adoption rates tend to increase proportionally with both the physical and economic size of farms. This trend is further reflected in specific production types - such as cereals, fodder crops, and vineyards - where the extensive nature of the former two may necessitate technological support, while the relatively higher revenue margins typical of vineyard operations may facilitate investment in A4.0 solutions. Certain solutions, such as monitoring systems and connected vehicles, have achieved higher acceptance, whereas others remain unexploited. The primary motivation for adopting A4.0 solutions is predominantly associated with macro-level farm management improvements, including enhanced forecasting capabilities and more effective control and management processes, rather than in-field operational efficiencies, such as optimising technical inputs and increasing machinery and equipment efficiency.

The analyses presented in this manuscript, which focus on the Italian agricultural sector, are broadly aligned with the findings of international research. For instance, as reported by the United States Department of Agriculture[4], in 2023, 27% of U.S. farms or ranches employed A4.0 solutions for crop management. Among the most widely adopted A4.0 solutions for crop management were automated guidance systems (covering 58% of planted acres), yield mapping (44%), Variable Rate Technology (37%), soil maps (22%) and drones and satellite imagery (7%) (United States Government Accountability Office, 2024[5]). Similarly, in Germany, a survey conducted on Bavarian farmers reported that the most widely adopted digital tools included weather and pests forecast models and apps (38%), digital field records (21%), automated steering systems (21%), maps from satellite data (14%), with an overall adoption rate estimated around 62% of the sampled agricultural enterprises (Gabriel and Gandorfer, 2023).

This study also underscored the benefits of A4.0 solutions, which were generally perceived as aligning with expectations, with some exceeding initial anticipations. This suggests a largely successful implementation among adopters. Notably, the areas where respondents reported the greatest benefits surpassing expectations were related to the optimisation of technical inputs and water management. Consistent with the findings of Zul Azlan et al. (2023), Abbasi et al. (2022), and Pradel et al. (2022), A4.0 solutions have demonstrated the potential to assist farmers in reducing input and water consumption, thereby generating both economic advantages through cost reduction and environmental benefits. Regarding the potential social sustainability benefits, Italian farmers have identified "streamline and optimise workforce processes" among the ones more in line with expectations, with a small share of farmers pointing out that A4.0 solutions disappointed their expectations. The broader social sustainability implications of this perceived benefit remain debated in literature. Some studies suggest a positive evolution in the agricultural labour market, potentially improving farmers' livelihoods and creating new employment opportunities (e.g., Rotz et al., 2019). Other contributions, instead, underline the need for specific studies on the yet unexplored consequences on the agricultural labour market originated from the optimisation of farming activities, potentially reducing the demand for unskilled workers (Rotz et al., 2019; Rose et al., 2021).

Nevertheless, despite the perceived benefits of A4.0 solutions, their implementation remains constrained by several challenges. These include interoperability issues, lack of adequate skills, return on investment concerns and technical assistance limitations, which hinder correct A4.0 solutions implementation and their benefits. In addition, several financial and structural constraints emerge as significant deterrents for non-adopters. Among these, the lack of trust in A4.0 solutions appears to be the most critical barrier. This skepticism is often linked to a perceived low utility of A4.0, a belief that existing tools are sufficient to meet current needs, difficulties in assessing the potential benefits, and the generally small size of agricultural enterprises - factors that collectively slow digital adoption in Italian agriculture. Economic and financial obstacles seem to be less relevant: these include doubts about the feasibility of investments that depend on cost-sharing over time or across multiple farms, as well as limited access to incentives - often constrained by bureaucratic complexity (Cisilino

[4] https://downloads.usda.library.cornell.edu/usda-esmis/files/h128nd689/4j03fg187/fj237k64f/fmpc0823.pdf
[5] https://www.gao.gov/assets/d24105962.pdf

and Licciardo, 2022). These financial constraints pose a fundamental challenge particularly for small and medium-sized farms that may lack the capital required for initial investments in A4.0 solutions. This issue is further exacerbated by the uncertainty surrounding return on investment, making it difficult for farmers to justify the adoption of these solutions without clear and measurable long-term economic benefits. In contrast, technical challenges appear to be less influential: only a minority of non-adopters cite inapplicability to specific production processes, lack of technical skills, or insufficient expertise as reasons for avoiding A4.0 solutions. Moreover, connectivity issues emerge as a challenge for non-adopters, especially in marginal areas and on hills across Italian regions, thus limiting the implementation of A4.0 solutions, as highlighted by Sozzi et al. (2021). As also emphasised by Fragomeli et al. (2024) and Da Silveira et al. (2023), such obstacles significantly impede the broader adoption of A4.0 solutions by limiting both the willingness and ability of farmers to integrate these tools into their production systems. Furthermore, as highlighted by Gonzales-Gemio and Sanz-Martín (2025), the inequality in access to A4.0 solutions could hinder the adoption of sustainable agricultural practices. Digital platforms and monitoring solutions, for instance, have the potential to substantially enhance the efficiency of carbon farming initiatives and contribute more broadly to agricultural sustainability.

These findings are consistent with an analysis published by the General Secretariat of the Council of the European Union[6], which emphasizes that - compared to other sectors - the pace of digital adoption in agriculture has been slower. This lag is attributed to several interrelated factors, including inadequate infrastructure, substantial upfront investment requirements, a widespread lack of digital skills, and the inherent complexity of the agricultural sector. The latter includes considerable variability in climate conditions, soil types, crop systems, and farming practices, all of which pose additional challenges to the effective implementation of A4.0 solutions.

The findings of this study are also aligned with emerging academic literature on the barriers to A4.0 adoption within the Italian agricultural sector. For example, Addorisio et al. (2025), based on interviews with Italian farmers, underscore the critical role of stakeholder cooperation and targeted training initiatives in addressing key impediments to adoption. These include limited interoperability among A4.0 solutions, insufficient digital competencies, and a lack of adequate technical support. Similarly, Giorgio et al. (2024) explore perceived advantages and challenges associated with digitalisation in Northern Italy. Reported benefits include enhanced environmental sustainability, improved input efficiency, reduced labour requirements, and lower operational costs. However, the study also identifies persistent barriers such as limited digital skills, inadequate data management practices and issues with interoperability. These findings suggest that policies should not only support equipment acquisition, but also promote the development of farmers' human capital.

Addressing these challenges through targeted policy interventions, comprehensive training initiatives, and improved system interoperability could substantially enhance A4.0 adoption rates, thereby ensuring that a broader range of agricultural enterprises benefits from the efficiencies and advancements offered by digital innovations. Moreover, collaboration among policymakers, technology providers, and industry stakeholders is crucial in fostering an ecosystem that supports seamless integration, mitigates adoption barriers, and maximizes the impact of digital agricultural innovations.

CONCLUSIONS

This study offers valuable empirical insights into the current state of Agriculture 4.0 (A4.0) adoption in Italy, shedding light on drivers influencing the uptake of A4.0 solutions, the perceived benefits, the challenges met by farmers who adopted A4.0 solutions and the barriers that prevented other agricultural enterprises from adopting A4.0 solutions. By disaggregating results according to critical variables related to farms (size, primary crop production and geographical localisation), this research contributes to a more nuanced understanding of how the A4.0 paradigm is taking root within the Italian agricultural sector. These findings provide a strong empirical foundation for informing public policy, guiding investment strategies and designing initiatives that are tailored to the needs of diverse farming profiles.

Specifically, the results highlight the importance of structural variables such as farm size, crop production and turnover in shaping adoption patterns, suggesting that public support mechanisms should be differentiated accordingly. Small farms, which tend to face greater barriers in terms of investment capacity and technical know-how, may benefit from targeted subsidies, tax incentives, and digital infrastructure improvements, particularly in under-served rural regions. Moreover, the limited adoption of certain A4.0 solutions underscores the need for broader outreach, technical assistance and knowledge transfer mechanisms to ensure that innovation diffuses

[6] https://www.consilium.europa.eu/media/shxiaxmo/2024_971-art-agriculture-11-02-25.pdf

beyond a small subset of more-structured farms. Training programs should also be adapted to the varying levels of digital literacy across the sector, with modular content suited to both entry-level and experienced users.

Moreover, by identifying which types of farms might be most likely to adopt A4.0 solutions and which barriers inhibit the uptake of digital tools, technology providers can refine their product design, marketing strategies, and sales services. Companies may, for instance, enhance interoperability and user-friendliness to address common usability challenges.

A promising avenue for future research would involve a comparative analysis of the levels of A4.0 adoption, associated needs, benefits, challenges, and barriers identified in this study with those observed in other European countries and beyond.

Another potential research direction could focus on examining the impact of A4.0 solutions on economic, environmental, and social sustainability to comprehensively assess the costs and benefits of A4.0 implementation. This analysis could, in turn, contribute to bridging the gap between adopting and non-adopting agricultural enterprises.

Nonetheless, these contributions should be considered in light of the following methodological limitations arising from the survey administration method and the sample distribution compared to the reference population. As with all Computer-Assisted Web Interviewing (CAWI) methods, this online survey may exclude individuals without internet access or those less comfortable with technology. Additionally, self-selection bias could skew the results, as participants are likely to be those with an interest in the topic or familiarity with online surveys. Consequently, adoption rates of A4.0 solutions reported in this study may be overestimated, while the perceived benefits and willingness to invest further in digital technologies could reflect the attitudes of a smaller group of more innovation-oriented farmers. Addressing these limitations in the future research would require efforts to reach less digitally-involved segments of the Italian agricultural sector to enhance the external validity of the findings.

Moreover, the discrepancy between the sample size distribution and the population size distribution leads to an overrepresentation of farms in the North and an underrepresentation of those in the South and Islands, potentially introducing a geographical bias. Furthermore, the average UAA (Utilised Agricultural Area) of the sampled farms (22 hectares) is significantly higher than the figure reported by ISTAT[7] (11.1 hectares), suggesting a selection of more structured agricultural enterprises. Additionally, the greater representation of the vineyard sector, which is characterised by higher-than-average profitability and greater spending capacity, could influence this study's findings.

[7] https://www.istat.it/it/files/2022/06/censimento_agricoltura_gismondi.pdf

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Agritech policy landscape: Insights from relevant stakeholders on policy issues and strategic plans in Italy

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Abstract. Agricultural practices face growing challenges, including climate change, resource constraints, meeting sustainability goals and food security. This study examines stakeholder perspectives on smart farming technologies and their integration into policy frameworks. A mixed-method approach, using triangulation of qualitative and quantitative data, combines an online survey (targeting experts from academia, industry, and policymaking) distributed through the Agritech project network and face-to-face interviews (engaging key stakeholders with in-depth knowledge of agricultural policy and technology implementation). Key findings reveal significant optimism about the potential of smart technologies to enhance efficiency, sustainability, and productivity in agriculture. However, widespread adoption is hindered by barriers such as high initial investment costs and a lack of technical knowledge. The study identifies policy gaps and provides actionable recommendations, including financial incentives, capacity-building initiatives, and improved infrastructure, to support the integration of these technologies. The findings underscore the critical need for adaptive policies that align with the evolving landscape of agricultural innovation, ensuring equitable access and long-term sustainability.

Keywords: Agritech, technology adoption, European agricultural policy, sustainability, stakeholders' perspectives.

1. INTRODUCTION

The global agricultural sector faces increasing challenges in balancing productivity, sustainability, and environmental responsibility. Climate change and resource constraints are putting increasing pressure on agricultural systems, whereas food security remains a multifaceted challenge that goes beyond production. Ensuring stable access to affordable, nutritious food also depends on market structures, distribution networks, and social inclusion (FAO, 2021). While technological innovation can support more efficient and sustainable production, it must be embedded within broader strategies that address systemic barriers to food security (FAO, 2021; IPCC, 2023). Given the limitations of arable land and the growing demand for sustainable food production, smart agriculture technologies are gaining recognition

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as a key driver of transformation. These technologies, encompassing sensor-based systems, IoT configurations, AI applications, and renewable energy solutions, offer advanced tools for precision farming, real-time monitoring, and resource optimization (Basso and Antle, 2020; Finger et al., 2019; Knierim et al., 2019). However, their adoption remains low and uneven despite their potential, primarily due to high initial costs, limited technical knowledge, and inadequate infrastructure (Akimowicz et al., 2021). These barriers are particularly pronounced for small and medium-sized farms, which often lack the necessary resources and institutional support to implement such technologies effectively.

Recent research by Menozzi et al. (2023) also highlights that farmers' decisions to engage in sustainability practices are shaped not only by economic incentives but also by behavioral drivers, such as perceived control and peer influence. In the case of digital agriculture, these behavioral aspects, especially regarding trust in digital systems and ease of use, are equally important and deserve policy attention.

Complementing this view, Giampietri et al. (2020) emphasize the role of trust in intermediaries and institutional transparency in shaping farmers' willingness to adopt CAP-subsidized risk management tools. While their study addresses instruments like insurance and mutual funds, our work extends this behavioural framing to digital agriculture, where trust also involves confidence in data systems and algorithm-based decision-making. While these behavioral dynamics were not the primary focus of our empirical study, they provide a valuable conceptual lens through which to interpret stakeholder concerns around adoption.

A well-structured policy environment is critical in facilitating the adoption of smart agriculture technologies. Policies that support financial incentives, training programs, and rural infrastructure development can significantly enhance accessibility and encourage broader implementation among diverse farming operations (Détang-Dessendre et al., 2018). While existing frameworks, such as the Common Agricultural Policy (CAP), the Green Deal, and the Farm to Fork Strategy, emphasize the role of innovation in agricultural sustainability, they exhibit notable gaps in addressing key adoption barriers. For instance, the CAP's current funding mechanisms primarily benefit large-scale farms with greater financial capacity, leaving smallholders with limited access to grants and subsidies necessary for adopting high-cost digital technologies (Lovec et al., 2020). Additionally, despite the Green Deal and Farm to Fork Strategy highlighting the need for sustainable agriculture, they fall short in prioritizing investments in rural digital connectivity, an essential component for integrating smart technology, particularly in remote agricultural regions (Ehlers et al., 2022). There is a need for proactive and adaptive policy approaches that address both financial and technical barriers while fostering stakeholder collaboration and long-term sustainability.

This study aims to examine stakeholder perspectives on the adoption challenges and opportunities of smart agriculture technologies and identify policy interventions that can facilitate their broader integration. Using a mixed-method approach, the research combines qualitative interviews with key stakeholders and a quantitative online survey to gather diverse insights on the policy landscape, adoption barriers, and potential solutions. The analysis applies triangulation between the qualitative and quantitative findings to strengthen the interpretation of results and ensure that policy recommendations are grounded in multiple sources of evidence. The findings contribute to the existing literature by bridging the gap between technological advancements and policy implementation, providing evidence-based recommendations to enhance the diffusion of technology in agriculture.

This study is part of the Agritech project, a national research initiative funded by the Italian National Recovery and Resilience Plan (PNRR) that brings together universities, research institutions, and industry stakeholders to foster innovation in precision agriculture, AI, and sustainable farming. Conducted within Spoke 3, which focuses on policy frameworks and governance for smart agriculture adoption, this research builds on prior project activities that mapped key actors in the innovation ecosystem and developed targeted engagement strategies (AGRITECH, 2023). The stakeholder database, created in the framework of the project, enabled the distribution of our questionnaires through a trusted and well-informed network, ensuring policy-relevant insights from diverse, experienced participants across academia, industry, and policymaking.

The paper first describes the methodological framework, detailing the qualitative and quantitative data collection and analysis approaches. It then presents key findings, highlighting stakeholder perspectives on the benefits and challenges of smart agriculture technologies. The discussion explores the broader implications for policy and practice, focusing on the need for strategic policy interventions to overcome adoption barriers. Finally, the study concludes with recommendations for future research and actionable policy measures to foster a more supportive environment for smart agriculture innovation.

2. METHODOLOGY

2.1. Overview

To comprehensively assess stakeholder perspectives on smart agriculture technologies, this study employed a mixed-method approach, integrating qualitative and quantitative data collection techniques. This methodological choice is well-suited for exploring complex issues such as technology adoption in agriculture, as it allows for in-depth insights from expert stakeholders while also capturing broader trends in the sector (Creswell & Clark, 2017; Fielke et al., 2020). The combination of qualitative interviews and a structured online survey aims to strengthen the study's analytical depth by triangulating stakeholder perceptions across different backgrounds and levels of expertise.

Given the exploratory aim of this research and considering the quantitative sample size, the survey quantitative data primarily serve to identify general trends and perceptions rather than provide statistically robust conclusions. This quantitative approach is complemented by the qualitative interviews, which offer deeper, context-rich insights. By combining both qualitative and quantitative data, we follow an established methodological practice known as triangulation, enhancing the reliability and validity of our findings through cross-verification (Fetters et al., 2013).

The review of the existing literature revealed that previous research has often examined technology adoption in agriculture from either a purely economic or behavioral perspective. The focus of this study is to integrate policy dimensions and directly involve stakeholders from multiple sectors, including academia, technology providers, policy institutions, and farmers' associations. This holistic approach, which explicitly links technological innovation with policy development, represents a novel contribution to the existing body of literature.

The study focused on stakeholders in Italy. While Emilia-Romagna, one of Italy's most technologically advanced agricultural regions, was the starting point of the stakeholders' mapping, the survey distribution and interviews also involved participants from other key agricultural areas such as Puglia, Lombardia, and Veneto. This broader geographical engagement allowed the research to capture a more representative view of the national smart agriculture policy landscape.

Both qualitative and quantitative components of the study shared a common core of thematic focus, centering on:

- The barriers and drivers of smart agriculture technology adoption.
- The role of existing policies in shaping adoption trajectories.
- The perceived needs for policy innovation to facilitate broader uptake.

These dimensions were used both to frame the design of the survey and interviews and to guide the interpretation of findings in the results and discussion sections. Rather than formal hypotheses, they function as thematic pillars for an exploratory investigation into how policy, behavior, and technology interact in the current agricultural innovation landscape.

This methodological design aims to ensure a holistic assessment of the policy landscape surrounding smart agriculture technologies, while providing valuable insights for both academic discourse and policy formulation.

2.2. Qualitative data collection

The qualitative phase focused on gathering comprehensive insights from experts with extensive knowledge of smart agriculture technologies and policies. It was essential to understanding the barriers and opportunities surrounding the adoption of these technologies. A semi-structured interview format was used to ensure a structured approach, allowing for a mix of predefined questions and open-ended discussions. This approach provided a comprehensive view of stakeholder experiences, enabling the identification of key themes related to technology adoption and policy needs.

In-depth qualitative interviews were conducted with carefully selected experts in smart agriculture technologies and policy. These interviews were designed to elicit rich, detailed insights from highly experienced individuals. Although the final sample comprised five (5) participants, The decision to proceed with these interviews was taken based on the principle of thematic saturation, that is, the point at which no substantially new insights emerge from additional interviews (Guest et al., 2006). Given the specificity and expertise of our respondents, the interviews provided consistent and robust information across key themes. This approach aligns with accepted qualitative research standards, where small, purposively selected samples are typical and appropriate for exploratory, expert-based investigations (Creswell, 2013).

The questionnaire was designed based on the Agricultural Knowledge and Innovation System (AKIS) framework, which highlights the importance of multi-actor collaboration in agricultural innovation. It was structured into five main sections: (1) the respondent's background and expertise, (2) their perspectives on smart agriculture technologies, (3) challenges related to adoption, (4) awareness and evaluation of current policies, and (5) recommendations for improving policy support. This structured design ensured that responses covered both technical and policy-related dimensions, making this phase a crucial foundation for the overall study.

Participants were selected through a purposive sampling approach, ensuring that only individuals with significant expertise and direct involvement in the field were included. The selection process was based on a stakeholder mapping exercise carried out earlier in the Agritech project. Experts were identified from three key groups: public sector representatives involved in agricultural policy, academic researchers specializing in precision agriculture and rural policy, and industry professionals working with smart agriculture technologies and farmer cooperatives. This targeted selection process ensured a diverse yet highly relevant sample, strengthening the credibility of the findings.

Interviews were carried out face-to-face whenever possible, allowing for detailed discussions and clarifications. In cases where in-person meetings were not feasible, remote interviews were held. Five key experts participated in this qualitative survey. Thematic and textual analysis was used to process the responses, identifying recurring themes and key insights. The results from this phase informed the refinement of the quantitative survey in the next stage of data collection, ensuring that the study captured both broad trends and in-depth perspectives.

2.3. Quantitative data collection

The second data collection phase involved an online questionnaire to capture broad stakeholder perspectives on smart agriculture technologies, their adoption, perceived benefits, policy awareness, and associated challenges. This structured survey was designed to complement the qualitative insights gathered in the first phase by providing quantifiable data to identify patterns and validate expert opinions. The integration of both qualitative and quantitative methods was an attempt to ensure a comprehensive and balanced understanding of the key factors influencing the adoption of smart agriculture technologies.

The online questionnaire was adapted from the qualitative questionnaire, and structured into multiple sections, each addressing a critical aspect of technology adoption and policy implications. The first section focused on general respondent information, including their professional background, sector of activity, and geographic location, allowing for an analysis of how perspectives varied across different stakeholder groups. The second section examined familiarity and involvement with smart agriculture technologies, prompting respondents to indicate their level of knowledge and direct engagement with specific technologies, such as robotics, IoT, AI, renewable agri-systems, and spectral technologies. The third section examined the perceived contributions of these technologies, evaluating opinions on their potential to improve agricultural productivity, resource efficiency, environmental sustainability, and labor optimization.

A key component of the questionnaire was its focus on policy awareness and barriers to adoption. Respondents were asked whether they were aware of existing policies that support smart agriculture technologies, providing insights into the effectiveness of current policy communication and identifying gaps where improved dissemination of information might be needed. Additionally, the survey investigated major obstacles preventing the widespread adoption of these technologies, including financial constraints, technical knowledge gaps, regulatory barriers, and infrastructure limitations. The final section solicited policy recommendations, encouraging respondents to suggest changes to existing policies or propose new policy instruments that could facilitate the integration of smart agriculture technologies into mainstream agricultural practices.

The questionnaire was strategically distributed across multiple channels to ensure a high-quality and representative dataset. It was shared within the Agritech project network, reaching academics and researchers with expertise in agricultural policy, technology, and innovation. It was also circulated among stakeholders from the previously established project stakeholders' network, including policymakers, industry representatives, farmers' associations, and technology developers, potentially reaching over 90 persons. This distribution strategy was designed to maximize diversity in respondent backgrounds while maintaining a high level of expertise in the responses collected.

The sampling approach was purposive, targeting individuals with direct experience and informed perspectives on adopting smart agriculture technologies. Rather than aiming for a large random sample, the focus was on obtaining high-quality responses from knowledgeable stakeholders whose input could provide valuable insights into policy needs and adoption challenges. A total of 35 responses were collected, and after applying validity criteria, 20 responses were retained for final analysis. While this sample size may appear modest for a quantitative survey, it is consistent with expert-elicitation methods in policy and innovation research, where depth of knowledge and professional insight are prioritized over statistical representativeness (Baker et al., 2013).

The criteria for inclusion ensured that responses were complete, internally consistent, and provided by individuals with relevant expertise in the field of smart agriculture. Validity was assessed based on completeness, consistency, and relevance to the research topic. Responses that were incomplete, contained inconsistencies, or came from participants with no clear connection to smart agriculture were excluded. Both the online questionnaire and the qualitative interviews were conducted in parallel in the same period of time.

Rather than claiming statistical generalizability, the primary goal of the quantitative data is to highlight general patterns, stakeholder perspectives, and areas needing policy attention. These quantitative insights are therefore exploratory and are critically supported and contextualized through the qualitative findings obtained from in-depth expert interviews, ensuring that the interpretations are robust and contextually meaningful.

While the sample size of five qualitative interviews and 20 valid quantitative responses may appear limited, it is justified by the methodological rigor applied in the selection and analysis processes. The qualitative interviews were conducted with carefully selected key stakeholders representing different sectors of agriculture, including policy, research, and industry, ensuring expert-driven insights. Thematic saturation was reached, as no significantly new themes emerged in later interviews, suggesting that the core challenges and opportunities had been effectively captured (Baker et al., 2013).

For the quantitative survey, although the response count is modest, it reflects targeted participation from experienced stakeholders within the Agritech project network and a pre-established stakeholder database. The respondents' expertise ensured high-quality, informed perspectives, making the findings valuable for understanding adoption trends and policy needs. Future research could expand the sample size to further validate the findings.

2.4. Data analysis

The analysis of the collected data followed a structured multi-step approach, integrating both qualitative and quantitative methodologies to ensure a comprehensive interpretation of stakeholder perspectives on the adoption of smart agriculture technology and policy needs. Given the mixed-methods nature of the study, different analytical strategies were applied to the qualitative and quantitative datasets to maximize the depth and reliability of insights.

The qualitative data obtained from face-to-face interviews were manually analyzed using a combination of textual synthesis and thematic analysis. This approach was chosen to extract detailed insights from expert responses while maintaining the depth and context of qualitative feedback. In particular, thematic analysis involved identifying recurring patterns in the responses related to technology adoption, policy gaps, financial constraints, and regulatory needs (Kiger & Varpio, 2020). While the analysis was primarily descriptive, it provided structured insights into the challenges and opportunities surrounding each specific smart technology developed in the Agritech project. The responses were synthesized into key themes aligned with the study's focus, ensuring stakeholders' perspectives on technology diffusion, policy barriers, and suggested interventions were effectively captured.

To ensure a structured interpretation of the qualitative data, insights were categorized into two main dimensions. The first focused on technology-specific insights, where each smart technology of the Agritech project, namely: IoT, AI, sensor-based systems, and robotics, was examined separately. Responses highlighted perceived benefits, adoption challenges, and policy needs unique to each innovation. The second dimension analyzed the broader policy environment, capturing stakeholder views on existing policy frameworks, gaps in regulatory support, and recommendations for improving policy measures. This approach ensured that the qualitative findings were systematically organized, aiming to understand stakeholder perspectives.

Given the exploratory purpose and the sample size, the quantitative data obtained from the online survey were analyzed in XLSTAT using basic descriptive statistical methods (frequencies, percentages, and cross-tabulations) to highlight general trends and stakeholder perceptions regarding smart technology adoption, rather than conducting in-depth statistical tests. Frequency distributions were used to summarize categorical variables such as familiarity with specific technologies, perceived benefits, policy awareness, and adoption challenges. Cross-tabulations were applied to compare stakeholder perspectives across different professional sectors. Additionally, mean and standard deviation calculations were used to analyze responses on Likert-scale questions, assessing attitudes toward policy effectiveness, investment challenges, and knowledge dissemination needs.

The findings from the quantitative analysis provided a broad overview of key trends in technology adoption and policy perceptions. These insights were cross-referenced with the qualitative findings to ensure that the study's conclusions were supported by both in-depth expert opinions and a wider range of stakeholder perspectives.

3. RESULTS

The presentation of results follows the dual structure of our research design, distinguishing between general (cross-cutting) trends observed across stakeholders from the online survey (Section 3.1) and technology-specific insights derived from expert qualitative interviews (Section 3.2).

3.1. Cross-cutting perspectives on smart technology adoption

3.1.1. Geographic distribution and professional sectors of the online survey

The geographic distribution of online respondents shows a balanced representation from Italy's major agricultural regions (figure 1), with the highest representation from Emilia Romagna (46%), followed by Puglia (36%), and smaller contributions from Lombardia and Veneto (9% each). This distribution indicates a blend of perspectives from key agricultural areas, offering insights into potential regional variations in technology adoption and policy needs within the smart technologies sector.

In terms of professional sectors, the respondents represented a broad spectrum within the agricultural and smart technologies domains (figure 2). Approximately 33.33% of participants were involved in agricultural technology, including roles related to software development and research in precision agriculture. Another 33.33% came from academic backgrounds, emphasizing the importance of research-driven insights in advancing smart technologies solutions. Direct farming operations accounted for 12% of respondents, ensuring representation of the practical, on-ground perspective crucial to understanding adoption barriers. The remaining participants were involved in diverse areas, including professional training, technological transfer, manufacturing, and viticulture. This multifaceted representation highlights the need for cross-sectoral collaboration to create comprehensive and inclusive smart technology adoption policies.

The level of involvement with specific smart agriculture technologies varied among online respondents (figure 3). Sensor-based technologies emerged as the most familiar, with 31.82% of respondents indicating familiarity. Autonomous systems, AI, IoT, and nature-based renewable systems each garnered attention from 13%-18% of respondents, reflecting a broad interest in diverse smart agricultural innovations. Novel spectral interface technologies were the least familiar, with only 4.55% of respondents indicating involvement or interest, which could be attributed to limited applications or high implementation costs.

Online Respondents identified several primary contributions of smart technologies to the agricultural sector (figure 4). The leading perceived benefit was resource waste reduction, cited by 25.81% of participants as a crucial advantage. Closely following was the potential for reducing environmental impact, highlighted by 22.58% of respondents as a key benefit. Improved crop yields were also a prominent contribution, recognized by 19.35% of participants as a fundamental outcome of adopting smart technologies. Enhanced pest, as well as disease detection and increased labor efficiency were both identified as significant benefits, with each selected by 16.13% of respondents. Interestingly, none of the

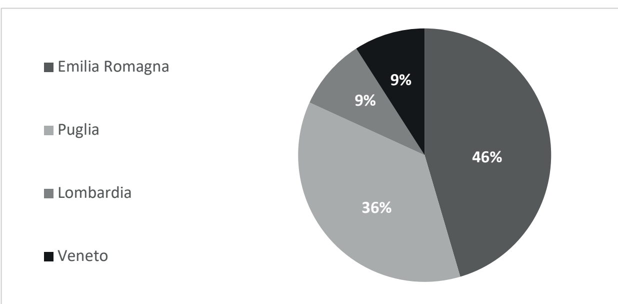

Figure 1. Geographic distribution of stakeholders.

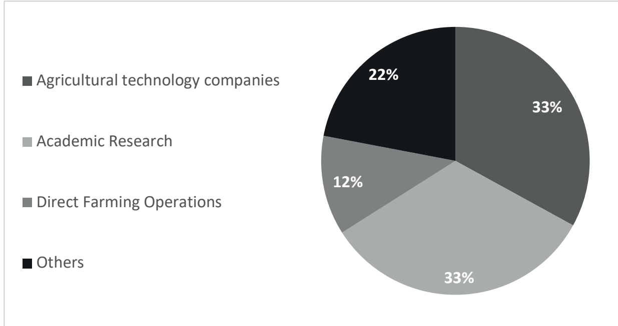

Figure 2. Professional Sector of the stakeholders.

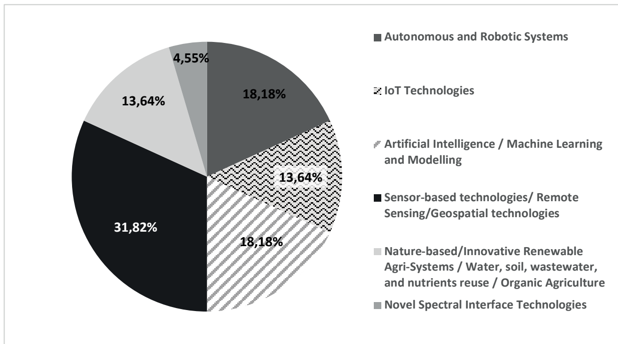

Figure 3. Key stakeholders' familiarity with Agritech project innovative technologies.

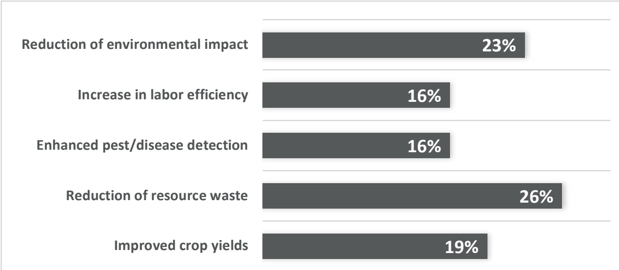

Figure 4. Contributions of innovative technologies to the agricultural sector, according to key stakeholders.

respondents chose the "Others" option, suggesting that the primary contributions listed were comprehensive enough to cover stakeholders' perceptions of the benefits of smart technologies.

3.1.2. Policy awareness and integration

The survey revealed varied levels of policy awareness among respondents. A substantial portion, 50%, expressed uncertainty regarding whether smart agriculture technologies are acknowledged within existing policy frameworks, suggesting a need for clearer communication on policy provisions. In contrast, 37.50% of respondents believed that relevant policies do exist, while 12.50% indicated an absence of any supportive policy. Several specific frameworks were noted among those who confirmed policy awareness, including PAC 2023-27, Agenda 2030, and precision farming policies. Additionally, respondents mentioned partial policy alignment with broader frameworks such as the Green Deal, Farm to Fork, and Soil and Biodiversity Strategies. This feedback highlights a fragmented policy environment where existing frameworks recognize the importance of innovation in agriculture but lack specific support for smart agriculture technologies.

Survey participants identified significant barriers impacting the adoption of smart agriculture technologies, primarily focusing on high initial investment costs and limited technical knowledge. 45% of respondents cited each of these factors, emphasizing the need for financial strategies and educational initiatives to address these challenges. Additionally, 10% of respondents noted limited infrastructure as an obstacle, highlighting the importance of developing robust infrastructure to support connected technologies like IoT. None of the respondents considered regulatory barriers an issue, suggesting that financial and knowledge-based obstacles are the most immediate concerns. These findings imply that while policies supporting smart agriculture technologies exist, they are not tailored to alleviate farmers' specific challenges, particularly small and medium-sized operations with limited capital and expertise.

Participants offered a range of recommendations for policy adjustments that could facilitate the adoption of specific smart agriculture technologies. For autonomous and robotic systems, respondents suggested financial incentives, such as non-repayable grants, and the diddemination of broader information to raise awareness. IoT technologies were identified as requiring targeted training programs, while AI and machine learning would benefit from a structured data-sharing framework and technical support to aid users in navigating complex algorithms. Sensor-based technologies require policies that focus on transforming raw data into actionable information, enabling farmers to make informed decisions based on real-time insights. For renewable agrisystems, respondents suggested training vouchers and regulatory adjustments to support organic and sustainable practices. These policy recommendations emphasize the importance of tailoring support mechanisms to the distinct requirements of each smart agriculture technology, thus enhancing both accessibility and usability.

Online survey respondents prioritized several key research questions to guide future policy development regarding smart agriculture technologies. Approximately 44.44% of participants identified "How can government policies foster innovation in agriculture?" as the most pressing question, signaling strong interest in government's direct role in driving technological advancements. Equally prioritized was "How can smart agriculture technologies be integrated into the existing agricultural system?" indicating that the practicalities of implementing new technologies within current systems are of critical concern alongside policy considerations. The importance of understanding the impact of existing policies on the adoption of smart agriculture technologies was also noted, with 11.11% ranking it as the primary concern and 44.44% ranking it as the second most important concern. Lastly, the collaboration between government and private sector stakeholders was noted as an area for future exploration, even if with lower priority. The diversity of opinions on this question suggests a balanced focus on government-led and collaborative initiatives.

The online survey also identified key stakeholders essential to the development of smart agriculture technologies policy, including farmers and academia (each cited by 25% of respondents), smart technologies companies (17.86%), public agencies, and large retailers (14.29% each). This distribution underscores the necessity of engaging diverse participants to create policies that address practical needs, market demands, and technological feasibility.

3.2. *Technology-specific insights*

The qualitative data gathered from the qualitative expert interviews provide a deeper understanding of stakeholder perspectives on specific smart agriculture technologies, their potential contributions, and the barriers that may hinder their adoption. The insights gained through these interviews underscore the diversity of challenges and recommendations within the smart agriculture technologies domain, offering nuanced perspectives that supplement the survey findings.

3.2.1. *Perspectives on robotic systems*

Stakeholders frequently highlighted the transformative potential of robotic systems in addressing labor shortages, a pressing issue particularly in labor-intensive areas such as fruit and vegetable production. Robotic technologies allow for precise management of tasks, from field crop monitoring to harvesting, which can significantly improve efficiency while reducing reliance on manual labor. This technological precision supports a shift toward sustainable practices, as robots can optimize resource allocation, minimize wastage, and even carry out tasks with environmental sensitivity in mind. However, stakeholders pointed out that the high costs associated with robotic systems pose substantial barriers to adoption, especially for small and medium-sized farms. The financial outlay required for these technologies and their technical complexity presents a formidable challenge for farmers without specialized knowledge or resources to support this transition.

To address these issues, stakeholders suggested targeted financial incentives, such as non-repayable grants or tax relief for farms adopting robotic systems. Furthermore, they advocated for broader policy adjustments to ease the learning curve associated with these technologies. Suggestions included on-site training programs, community equipment-sharing initiatives, and educational workshops that demystify the use of robotics in farming. From a policy perspective, interviewees indicated that while overarching strategies like the Green Deal and Farm to Fork acknowledge the importance of agricultural innovation, they lack specific provisions to support the adoption of robotics. By expanding precision farming policies to include robotics, policymakers could foster a more comprehensive approach to integrating these technologies into agricultural systems.

3.2.2. *IoT for resource optimization*

IoT technologies were recognized by stakeholders as essential for optimizing resource use, particularly in water management. By integrating IoT-enabled devices, farmers can collect real-time data on soil moisture, crop health, and environmental conditions, allowing for precise irrigation adjustments that conserve water and reduce costs. Beyond individual farm benefits, stakeholders noted that the data generated by IoT systems could support broader agricultural analytics, improving forecasting and resource management on a regional or even national level (Weersink et al., 2018).

Despite these advantages, stakeholders expressed concerns over the cost and interoperability of IoT systems, which can make adoption challenging, particularly for smaller farms. The lack of standardized protocols for data sharing among different IoT devices presents another barrier, as farmers often require an integrated view of data across multiple devices and systems. To address these issues, stakeholders recommended policy interventions to promote data-sharing standards and compatibility protocols to enable seamless integration across IoT platforms. Additionally, they advocated for reducing bureaucratic complexities surrounding IoT implementation, which could encourage more farms to adopt IoT configurations and benefit from their potential efficiencies.

3.2.3. *Sensor platforms and remote sensing technologies*

Sensor technologies, particularly those designed for unmanned or automated configurations, were identified as having significant potential to enhance agricultural efficiency. These technologies allow for precise management of resources like water and nutrients and provide real-time monitoring that supports effective disease control and overall crop health management. For example, by using soil moisture sensors, farmers can optimize irrigation schedules, reducing water use without compromising crop quality. Additionally, the environmental benefits of sensor-based systems are considerable, as they minimize the need for excess inputs, thereby lowering the environmental footprint of agricultural operations.

However, stakeholders noted that sensor platforms face barriers similar to those of other advanced technologies, including high installation costs, technical limitations, and the need for specialized training. Furthermore, respondents pointed out that the absence of a unified data platform for sensor integration complicates data interpretation, making it challenging for farmers to convert raw data into actionable insights. To support the adoption of sensor technology, stakeholders suggested policy adjustments that include infrastructure investments, such as broadband expansion to rural areas and establishing public-private partnerships for data platform development. These initiatives could facilitate real-time data aggregation and analysis, allowing farmers to maximize the benefits of sensor platforms for sustainable agriculture.

3.2.4. Role of artificial intelligence and machine learning in agriculture

Artificial Intelligence (AI) and Machine Learning (ML) technologies hold transformative potential for agriculture, enabling real-time analysis and predictive insights that enhance decision-making and resource allocation. AI-driven applications allow farmers to monitor crop health, predict yield outcomes, and optimize input use, making farm management more efficient and responsive. Stakeholders believe that AI could streamline processes across the agricultural value chain, from planning and planting to harvest and market delivery, thereby adding value at each production stage.

Despite this promise, AI adoption in agriculture is restricted by several challenges. First, the high costs associated with AI solutions can be prohibitive, particularly for smaller operations. Second, data interoperability presents technical challenges, as different AI applications often require diverse data inputs that may not be readily compatible with each other. Lastly, stakeholders highlighted the complexity of using AI solutions, which often require advanced technical knowledge that may be inaccessible to many farmers. Recommendations for policy interventions included establishing open data systems, which could facilitate data sharing across AI platforms, and government-supported training programs that simplify the use of AI. Additionally, respondents advocated for technical support mechanisms to help farmers navigate AI applications and fully realize their potential benefits.

3.2.5. Nature-based solutions and renewable agriculture

Stakeholders emphasized the growing importance of nature-based solutions, such as water and soil reuse, nutrient recycling, and organic farming practices, as essential components of sustainable agriculture. These renewable systems reduce environmental impact by reducing reliance on synthetic inputs and fostering a more balanced relationship between agriculture and the environment. Nature-based solutions promise healthier soils, improved crop resilience, and long-term sustainability, making them an attractive alternative for farmers aiming to minimize their ecological footprint.

However, the transition to renewable agri-systems is not without challenges. Stakeholders noted that high initial investment costs, limited expertise, and regulatory inconsistencies are significant barriers. To address these challenges, respondents recommended that policies provide financial incentives, such as subsidies for transitioning to organic farming and grants for infrastructure investments. Training programs focused on sustainable farming practices and more robust certification systems were also suggested to ensure market recognition of organic and nature-based products. By supporting these transitions, policymakers can promote a more sustainable agricultural model that aligns with environmental goals.

3.2.6. Novel spectral interface technologies

While novel spectral interface technologies, including microwave and THz radiation applications, were less familiar to many respondents, some stakeholders acknowledged their potential for non-invasive agricultural monitoring. These technologies allow for detailed analysis of crop health, soil composition, and other critical indicators without physical contact, which could prove valuable for precision agriculture. However, the application of spectral technologies faces unique challenges, including high costs, safety concerns related to radiation use, and the need for specialized expertise to interpret complex data.

Stakeholders recommended targeted policy interventions to address these challenges. Suggestions included funding for research focused on agricultural applications of spectral technologies, safety standards to ensure that radiation use does not pose health risks, and farmer training programs to build competence in spectral data interpretation. Additionally, respondents expressed interest in exploring integrating spectral data with AI, which could improve data analysis and support more efficient agricultural decision-making.

4. DISCUSSION

The findings of this study reinforce the well-documented potential of smart agriculture technologies to address pressing challenges in the agricultural sector, such as resource efficiency, climate adaptation, and sustainability. These technologies, when the right conditions are met, also play a growing role in building food system resilience by improving productivity and reducing losses, particularly under climate stress, as reported by Gemtou et al., (2024). Despite this potential, adoption remains limited due to financial, technical, and infrastructural constraints. These results align with previous research, which emphasizes that economic barriers and knowledge gaps are among the most significant obstacles to the adoption of technology in agriculture (Basso & Antle, 2020; Finger et al., 2019). However, the findings also highlight a critical gap in policy awareness, which has received less attention in the existing literature but emerged as a key concern among stakeholders in this study.

One of the particularities of this research lies in its mixed-methods approach, which combines qualitative depth with exploratory quantitative insights. While the number of responses in the survey is modest, the alignment between the survey trends and the interview narratives provides a form of triangulation that enhances the robustness of the results. This integration allowed us to validate emerging patterns, ensuring that the insights are not reliant on a single data source but are reflected across multiple forms of stakeholder engagement (Fetters et al., 2013; Creswell & Plano Clark, 2017). The triangulation design was particularly valuable for assessing the adoption barriers and policy dynamics around smart technologies, where numerical trends were consistently reinforced by expert perspectives.

This convergence of evidence across the two methods strengthens confidence in the relevance of the results. One of the most striking of these results is the widespread lack of clarity regarding the role of existing policies in supporting smart agriculture technologies. Many respondents expressed uncertainty about whether current frameworks, such as the Common Agricultural Policy (CAP) 2023–2027, the Green Deal, and Farm to Fork, sufficiently address the specific needs of technological adoption in agriculture. This reflects findings from previous studies indicating that while sustainability and innovation are often mentioned in high-level policies, their implementation at the farm level is often fragmented and unclear (Candel, 2022; Rose et al., 2021). A key implication of this study is that policymakers must improve communication strategies to ensure that farmers, technology developers, and other stakeholders are well-informed about existing policy instruments and funding opportunities.

This lack of clarity is also linked to a broader issue of trust and how farmers perceive these policies. For instance, Giampietri et al. (2020) show that trust in intermediaries plays a critical role in adoption of CAP-subsidized risk management tools. Our findings suggest that in the context of smart farming, this trust must extend to digital service providers and data systems, highlighting the need for transparency, digital literacy, and certification mechanisms that can build farmers' confidence in technological tools.

Consistent with earlier research (Long et al., 2016; Weersink et al., 2018), this study also confirms that high initial investment costs remain a fundamental barrier to technology adoption. This is particularly problematic for small and medium-sized farms, which struggle to access capital for automation, AI-driven decision support tools, and IoT-enabled monitoring systems. The exploratory quantitative results highlighted the widespread concern about financial and technical barriers, and likewise, these survey insights were strongly supported by qualitative findings, where experts repeatedly emphasized similar barriers such as high upfront costs, limited access to financial resources, and difficulties accessing technical support. This cross-analysis between survey data and expert interviews strengthens the validity of our observations and highlights the need for targeted policy responses that directly address these barriers. While financial incentives, such as grants, tax credits, and low-interest loans, are already part of some policy frameworks, stakeholders expressed concerns that these incentives are often complex, difficult to access, or insufficient to offset adoption costs. Policymakers should consider simplifying administrative procedures for funding applications and targeting financial assistance toward the most impactful technologies identified in this study, such as sensor-based monitoring, AI-driven decision-making, and precision irrigation systems.

Additionally, as reinforced by both datasets, cost-sharing and infrastructure emerged as cross-cutting themes, underscoring their significance regardless of methodological lens. Stakeholders recommended public-private partnerships to support cost-sharing initiatives, particularly for expensive infrastructure investments, such as rural broadband expansion. These findings reinforce recent discussions on the role of co-financing mechanisms and innovation clusters in mitigating the risk associated with technology adoption for farmers (Ehlers et al., 2022).

A consistent finding across both data sources was the importance of technical knowledge and training in shaping adoption outcomes, consistent with previous studies (Charatsari & Lioutas, 2013; Lovec et al., 2020). Smart agriculture technologies often require specialized skills, yet many farmers have limited access to training programs that could help them integrate these innovations effectively. Stakeholders emphasized the need for structured, hands-on training initiatives that focus on technology usability, data interpretation, and integration into existing farming systems.

This highlights an important policy gap: while some funding exists for technology development, there is often insufficient investment in farmer education and capacity building. Policymakers should consider expanding agricultural extension services to provide in-person training, online courses, and demonstration farms where farmers can experience the benefits of digital agriculture firsthand. Knowledge transfer partnerships between research institutions and farming communities could also play a crucial role in reducing this barrier. This aligns with Menozzi et al. (2023), who emphasize that perceived behavioural control and attitudes are pivotal in shaping adoption decisions, especially when practices are unfamiliar or technically demanding. Similarly, our respondents stressed the difficulty of using AI or IoT platforms, reinforcing the need for support measures that go beyond finance to include training, usability, and peer-to-peer learning networks.

The study also highlights infrastructure limitations, particularly concerning internet connectivity in rural areas. Technologies such as IoT-based monitoring, remote sensing, and AI-driven decision support tools rely on high-speed internet and cloud computing, yet many agricultural regions lack the necessary broadband infrastructure. This issue is consistent with prior research, which emphasizes that the digital divide between urban and rural areas is a significant barrier to the diffusion of technology (Ehlers et al., 2022).

A broader finding from this study is that smart agriculture policies must be adaptive, responsive, and inclusive. Stakeholders reported that existing policies often fail to differentiate between the needs of different types of farmers, particularly smallholders versus large-scale agribusinesses. One-size-fits-all policy approaches may not be effective in promoting equitable adoption, suggesting the need for targeted support mechanisms.

Additionally, stakeholder engagement must be prioritized in policy design and implementation. The findings of the qualitative survey suggest that many policy frameworks lack farmer representation in the decision-making process, leading to misalignment between policy objectives and on-the-ground realities. To improve this, policymakers should, according to the key expert stakeholders, incorporate participatory approaches, such as co-design workshops, multi-actor innovation networks, and regional consultation forums.

While this study aims to provide valuable insights into the adoption barriers and policy needs of smart agriculture technologies, using triangulation, combining exploratory survey findings with detailed expert interviews, to provide a balanced and credible approach, in an attempt to make the insights more robust, certain limitations should be acknowledged. The sample size, particularly for the qualitative interviews, was relatively small, which may limit the generalizability of some findings. Additionally, the reliance on self-reported data introduces the possibility of response biases, as participants' perceptions may not always reflect objective realities. However, it is important to note that the study purposefully targeted key stakeholders, namely: policy experts, researchers, and technology developers, identified through a structured stakeholder mapping within the Agritech project. As such, the participants likely represent some of the most informed individuals on smart agriculture policy and technology in Italy, enhancing the relevance and depth of the insights gathered. Future research should explore larger and samples to validate these findings across different agricultural systems and geographic regions. Comparative studies examining policy effectiveness in multiple countries could offer deeper insights into best practices for supporting smart agriculture adoption.

5. CONCLUSION AND POLICY IMPLICATIONS

This study highlights the importance of policy frameworks in facilitating the adoption of smart agriculture technologies while revealing key barriers hindering their widespread implementation. The results emphasize stakeholders' strong optimism regarding these technologies' role in improving agricultural efficiency, sustainability, and resilience. However, the study also identifies three major obstacles: high investment costs, technical knowledge gaps, and inadequate infrastructure, all of which must be addressed through targeted policy interventions.

A critical takeaway from this research is the necessity for policy alignment and accessibility. While existing frameworks acknowledge innovation, a disconnect exists between policy provisions and stakeholder awareness. This highlights the need for simplified policy regulations, better communication strategies, and stronger engagement with the farming community. Policies should be designed to be practical, transparent, and adaptable, ensuring that they effectively support farmers and technology adopters in different agricultural settings.

Another key implication is the urgent need for financial instruments tailored to the realities of smart agriculture, Such as differences in farm sizes, digital readiness and access to broadband infrastructure, among others. Policies must focus on incentives such as subsidies, tax relief, and low-interest loans to lower the entry barriers for farmers, particularly small and medium-sized operations. At the same time, public-private partnerships should be expanded to create co-financing models that distribute investment risks across multiple stakeholders.

The role of education and technical training also emerges as a fundamental aspect of successful adoption. Smart agriculture technologies require specialized skills that many farmers currently lack. To address this, agricultural extension services should integrate digital training programs, on-field demonstration projects, and mentorship initiatives. Collaboration between universities, policymakers, and industry leaders can create structured knowledge-sharing platforms that provide ongoing support to farmers.

Finally, this study underscores the importance of an inclusive and adaptive policy-making approach. Engaging diverse stakeholders, from farmers to technology developers and policymakers, is essential for crafting policies grounded in real-world needs. Multi-actor governance structures, such as stakeholder consultation groups, regional innovation hubs, and participatory policy platforms, should be institutionalized to ensure that agricultural policies evolve in tandem with technological advancements.

In conclusion, smart agriculture technologies represent a transformative opportunity for the agricultural sector; however, their full potential can only be realized with robust, well-coordinated, and forward-thinking policies. Policymakers can accelerate the transition toward a more sustainable, productive, and resilient agricultural system by addressing financial constraints, bridging the knowledge gap, expanding digital infrastructure, and improving stakeholder engagement. Beyond economic and technological advancements, the successful integration of these innovations has profound implications for long-term sustainability and global food security. By improving resource efficiency, reducing environmental degradation, and enhancing adaptive capacity to climate change, smart agriculture technologies contribute to more resilient food systems that can meet the demands of a growing population. However, ensuring equitable access to these technologies is essential to prevent the widening of disparities between large-scale and smallholder farmers. Future policy efforts should focus on fostering inclusive innovation, integrating sustainability goals into technology adoption strategies, and aligning digital agriculture with broader climate and food security policies. By doing so, agricultural technologies can evolve in ways that not only drive economic growth but also ensure environmental sustainability and food system resilience.

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The potential of digital agriculture start-ups to reshape market dynamics in the ag-input industry: A case study from Argentina

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Abstract. Agri-food global value chains (GVCs) face growing pressure to enhance productivity and environmental sustainability, with technological innovation playing a critical role. In this context, start-ups have emerged as key innovation developers. This study provides a qualitative, exploratory analysis of the technological characteristics of 114 digital agriculture (DA) start-ups in Argentina. We have characterized their solutions and proposed implications for the industrial dynamics in agricultural input markets. Our analysis implies that most DA innovations tend to be complementary to existing technological packages rather than being disruptive. While these start-ups introduce innovative solutions, they currently seem to hold limited capacity to challenge the market dominance of large multinational agricultural input firms. By exploring the intersection of innovation and market structures, this study provides valuable insights into the evolving industrial dynamics of ag-input markets in agri-food GVCs. The findings offer strategic implications for start-ups, incumbents, and policymakers.

Keywords: start-ups, digital agriculture, innovation, industrial organization.

1. INTRODUCTION

Over the past decades, agri-food systems have undergone profound transformations driven by accelerated urbanization, technological change, and novel production techniques, resulting in significant gains in both productivity and food availability (Barrett et al., 2022; FAO, 2017; Reardon et al., 2019). However, global agri-food value chains (GVCs) continue to face substantial challenges related to addressing multiple imperatives: increasing food production for a growing global population, supporting agricultural-dependent emerging economies in their development trajectories, implementing more sustainable and efficient production practices that align with new social and environmental standards, and developing resilience to climate change impacts (Cerutti et al., 2023; Crippa et al., 2021; Yang et al., 2024).

In response to increasing pressure, we have seen in recent years the development of a large set of technologies aimed at enhancing the resilience of GVCs to potential shocks and steering them toward more sustainable trajectories (Costa et al., 2022; Wang et al., 2021). Unlike a few decades ago, when innovations were mainly concentrated in the R&D departments of large companies, today many innovations in this field are rooted in small technology-based companies and start-ups, known as *agrifoodtech* start-ups (Klerkx & Villalobos, 2024; Mac Clay et al., 2024). These companies, increasingly recognized as key players in the transformation of GVCs, offer solutions across the entire agri-food value chain, from upstream activities such as farming inputs and agricultural production, through food processing and distribution, all the way to downstream segments that connect with the end consumer. Among this large set of *agrifoodtech* start-up companies, a specific group is focused on providing digital agriculture (DA) solutions to the upstream segment of the value chain (McFadden et al., 2022, 2023; Wolfert et al., 2023), contributing to enhance farm-level data analysis, decision-making, and automation through technologies such as artificial intelligence, the Internet of Things (IoT), big data, robotics, sensors, remote sensing, platform technologies and blockchain, among others (Klerkx et al., 2019; Klerkx & Rose, 2020; Lezoche et al., 2020)[1].

In recent years, Latin America has witnessed rapid growth in the number of start-ups focused on food and agriculture, particularly in Brazil and Argentina, which account for 51% and 23% of these companies in the region, respectively (Bisang et al., 2022; Vitón et al., 2019). In particular, the dynamism of Argentina in this field can be attributed to a combination of factors. Externally, the country ranks as the world's third-largest net food exporter (World Bank, 2024). Internally, the agri-industrial sector explains 23.1% of the GDP and generates around 23% of private-sector employment (Ramseyer et al., 2024). Moreover, Argentina has pioneered in the adoption of agricultural technologies in the past, such as no-till farming (Peiretti & Dumanski, 2014; Scoponi et al., 2011) and genetically modified seeds (Qaim & Janvry, 2005; Qaim & Traxler, 2005), demonstrating a tradition of technological openness among farmers. Farmers are, on average, young (average age of 44 years) and highly educated (around 45% of farmers in Argentina have completed undergraduate or graduate studies), which favors the adoption of technology (FAO et al., 2021). Additionally, the availability of qualified professionals and entrepreneurial capacities seems to be fostering the development of *agrifoodtech* start-ups in the country (Lachman et al., 2022; Lachman & López, 2022; Navarro & Camusso, 2022).

However, beyond the promises and enthusiasm currently driving the innovative practices of these start-ups, there are critical aspects of political economy that determine the long-term fate of a technological innovation, which should not be overlooked (Hackfort, 2024; Prause et al., 2021). The scaling and success of a technological package do not depend exclusively on its intrinsic potential, as market and industrial dynamics will necessarily shape this process. Agricultural input markets currently exhibit high levels of concentration and market power, with a reduced group of companies wielding influence over commercial and technological trends (Fairbairn & Reisman, 2024; Mac Clay et al., 2024; Sauvagerd et al., 2024). Under this scenario, the promised transformation in agriculture risks being slowed down (or eventually thwarted) by incumbent strategies (Béné, 2022).

Despite a growing body of research analyzing the potential of new technologies in agri-food GVCs (Finger, 2023; Herrero et al., 2020, 2021; Meemken et al., 2024), little attention has been given to the dynamics of technological innovation within them, especially in developing countries, in which the development and commercialization of innovations pose additional challenges (Alam et al., 2023; Macchiavello et al., 2022). Overall, this work seeks to provide a preliminary perspective on how young start-up companies may reshape the market dynamics of the agricultural input industry and the implications for its future evolution. The main objective of this paper is to provide an exploratory analysis of whether digital agriculture (DA) start-ups have the potential to disrupt the industry structure in global agricultural input markets by challenging the dominant position of established multinational firms, particularly in the upstream segment of the value chain. We approach this question through a case study of Argentina, a relevant context due to its dynamic entrepreneurial ecosystem and strong presence of global agribusiness actors (Lachman et al., 2022; World Bank, 2024). We do this by characterizing the technological solutions offered by DA start-ups operating upstream at the farmer level[2], and by exploring how these solutions interact with the current technological standards set by incumbent companies in the agricultural input industry. The rationale behind focusing on the DA segment is that digital solutions have particu-

[1] This paradigm of accelerated innovation in the digital agriculture field is also known in the literature as Agriculture 4.0, Agri-food 4.0 or the Fourth agricultural revolution.

[2] We exclude companies offering solutions exclusively at the midstream or downstream level.

larly drawn the attention of agricultural input suppliers (such as seed, agrochemical, fertilizer, and machinery manufacturers) who view DA as a transversal technology across various activities in agricultural production (Lezoche et al., 2020). These companies also foresee DA as a potential enhancer of their current technological platforms in seed, crop protection, crop nutrition, and agricultural machinery segments (Fairbairn & Reisman, 2024; Kenney et al., 2020; Prause, 2021).

The remainder of this paper is structured as follows. In section 2, we describe the current industry structure of the agricultural input industry and the strategic actions incumbents are taking in the face of accelerating innovation in DA. In section 3, we present our conceptual framework, discuss the literature on interactions between established firms and start-ups in the context of accelerated technological change, and outline our two main analytical dimensions. In section 4, we present our methodological approach, and in section 5, we present the results of our analysis. In section 6, we discuss our results, exploring the central topic of the paper: whether DA start-ups change industrial dynamics in ag input markets. Overall, our analysis shows that most of the solutions developed by Argentine start-ups tend to be predominantly complementary to the existing technological packages, and this may represent an opportunity for dominant firms to strengthen their position either by acquiring or investing (as a way of technological exploration) in early-stage start-ups to incorporate those solutions into their own technological platforms. The last section of the paper presents conclusions and implications for different stakeholders.

2. THE AGRICULTURAL INPUT INDUSTRY IN THE FACE OF THE DIGITAL TRANSITION

Over the last three decades, concentration in agrifood GVCs has increased simultaneously in industries such as crop seeds, agrochemicals, fertilizers, agricultural machinery, and animal health and breeding products (Clapp, 2021; Fuglie et al., 2012; MacDonald, 2017; MacDonald et al., 2023). The path towards increasing market share has happened (mainly) through mergers or acquisitions (M&As), consolidating a small number of megacompanies that have led to GVCs' reconfiguring[3]. The implications of growing concentration in agricultural input markets and (its consequent increase in market power) have been explored in the literature by various authors, including Fuglie et al. (2012), IPES (2017), Deconinck (2020), Clapp (2022), and Béné (2022). Fuglie et al. (2012) note that the increase in market power resulting from this concentration can lead to higher input prices for producers. Furthermore, consolidation often limits options, favoring products that are more profitable for large companies (Clapp, 2021).

However, within the current technological paradigm driven by information and communication technologies (ICTs), DA solutions have sparked debate over whether this market dynamic of concentration can be disrupted. In the field of DA, many innovations originate from start-ups and small to medium-sized technology-based firms (Klerkx & Villalobos, 2024; Manganda et al., 2024). Over the last decade, we have witnessed a highly dynamic scenario of the creation of these types of firms, rooted in innovation ecosystems, which redefine relationships among traditional sector actors and introduce new business models based on digitalization and data access (Basso & Antle, 2020; Rotz et al., 2019).

Large incumbent companies that control the agricultural input markets are shifting toward incorporating digital solutions into their portfolios and adapting their business models to approach farmers with a more integrated, smart-farming approach. This is a limiting factor to start-ups' potential to disrupt industry structures. Incumbent companies are now pivoting from selling products to offering more integrated solutions, using digital tools within broader systems to incorporate data analytics, decision support, and automation, while strengthening oligopolistic dynamics by establishing collaborative and interconnected digital platforms, which may limit the access of new players (Sauvagerd et al., 2024). Seed and crop protection companies such as Bayer, Corteva, Syngenta, and BASF have developed proprietary platforms that enable farm-level decision-making based on real-time environmental and agronomic data. These systems, such as Bayer's *FieldView* or BASF's *xarvio* exemplify the shift towards offering service-based solutions that create data lock-ins and potentially redefine customer relationships (Jiang, 2021; Trivedi, 2022). Fertilizer firms are also going in the same line. Companies like Nutrien and Yara, for instance, use digital platforms to monitor field-level input application and promote practices related to precision fertilization, while large animal pharma incumbents have recently advanced in the acquisition of precision tools for livestock management and monitoring (e.g., Merck Animal Health acquired QuantifiedAg and Zoetis acquired Performance

[3] Examples include the 2015 merger of Dow and DuPont, resulting in Corteva Agriscience; ChemChina's acquisition of Syngenta in early 2016; and Bayer's subsequent purchase of Monsanto. This sector, already highly concentrated and dominated by the "Big Six" since the early 2000s, is now controlled by four major firms – Bayer, Corteva, Syngenta, and BASF. Something similar happens in the agricultural machinery sector, in which the four leading companies control around half of the market sales.

Livestock Analytics). Crop protection and nutrition companies are also investing in digital marketplaces that streamline the process of selling to farmers and create digital channels as a complementary solution to traditional distribution channels (for example, Yara and Syngenta are investors in the Argentine marketplace Agrofy).

Farm machinery manufacturers, including Deere & Co., CNH Industrial, Kubota, and AGCO, are investing in precision agriculture and smart machinery (Birner et al., 2021; Paolillo, 2022). These companies are integrating sensors and telemetry to improve the performance of their products, with a focus on automation and interoperability. They also offer services that enhance the value of the data collected by machinery. Moreover, commodity trading companies such as Cargill, ADM, and Louis Dreyfus are using digitalization to improve the transparency and traceability of their value chains. They provide digital tools to farmers to facilitate selling and adopt digital platforms to enhance their sourcing process.

Collectively, these actions indicate a systemic trend: dominant input firms are not only adapting to digital agriculture but also seeking to shape its institutional and commercial architecture. Based on the C4 concentration ratio (ETC Group & GRAIN, 2025), we summarize in Appendix 1 the initiatives of top companies in each significant segment related to DA. These are the actors most likely to influence the direction and structure of digital agriculture.

Considering the actions these companies are taking towards DA, the critical question that emerges is whether the evolving patterns of innovation and the novel technological solutions associated with DA that small firms are developing have the potential to disrupt the recent trend of market concentration in aginput industries or whether they will entrench existing patterns of consolidation further.

3. CONCEPTUAL FRAMEWORK

3.1. Interactions between incumbents and start-ups in the context of technological change

The features of new technologies and their relationship to incumbent firms' current technological standards not only influence production but also shape market dynamics, including strategy configuration, leadership, and governance (Mac Clay & Sellare, 2025). This is especially relevant in a context in which the cost of technological building blocks has been drastically reduced over the last decades, due to increases in computing capacity (Lundstrom & Alam, 2022) and reductions in genome sequencing costs (Song et al., 2023). What was once an exclusively internal process for large firms is now being reconfigured as a distributed innovation process, with smaller players entering the scene. Start-ups (and small- to medium-sized firms) hold greater ability and flexibility to explore emerging technologies first, in many cases with disruptive potential.

Start-ups can adapt quickly and flexibly to new business opportunities and are more likely to align incentives among entrepreneurs, investors, and employees (Bendig et al., 2022; Dushnitsky & Yu, 2022). In contrast, incumbents tend to focus on exploiting existing capabilities (Freeman & Engel, 2007). Thus, as start-ups have more dynamic rates of innovation, this may imply an opportunity for incumbents to outsource part of their R&D process by making corporate investments, acquiring start-ups, or forming partnerships within an open innovation framework, in interactive contexts such as business or innovation ecosystems (Berthet et al., 2018; Bogers et al., 2018).

While these advantages give start-ups some disruptive potential, their ability to challenge dominant industry positions can be mitigated by the response of incumbent firms, which are in control of the value chain and have the ability to set governance rules, as well as prioritize technology standards (Clapp & Ruder, 2020; Fairbairn & Reisman, 2024). Many novel technologies exhibit low marginal costs once they become commercially scalable but require substantial investments in the development phase (Zilberman et al., 2022). Start-ups often lack the necessary operational and financial resources, as well as market access, distribution channels, and brand recognition. Thus, for start-ups, partnering with large, established firms may be necessary not only to secure funds for technological development but also to secure future access to markets once the technology is viable. By interacting with start-ups, incumbents may be able to exploit a window of technology to incorporate promising solutions while reducing failure costs (Dushnitsky & Lenox, 2005). The possibility of engaging in open innovation processes is also critical for redefining corporate identity in rapidly evolving contexts (Waßenhoven et al., 2025).

This interaction between incumbents and start-ups may also give incumbent firms a way to control technological pathways, which is especially relevant in the context of high market concentration, as it happens in agricultural input industries (Béné, 2022). By investing in, acquiring, or entering into research partnerships with start-ups and emerging companies, these incumbents might find a way to control the type of technology that reaches the market (or even the pace of innovation). Moreover, some innovations tend to be systemic, requiring adaptations from different members of the value chain to be successful. In these cases, some industry incumbents need to step up and take leadership, promoting these technologies as the new standard, potentially leading to winner-take-all scenarios (Harryson & Lorange, 2024; Klerkx & Rose, 2020; Sauvagerd et al., 2024).

3.2. Dimensions of analysis: materiality and functional integration of innovations

To assess the extent to which emerging DA start-ups offering solutions to farmers in the upstream segment of GVCs can disrupt and reshape the highly concentrated agricultural input markets (as described in the previous section), this paper characterizes start-ups technologies and examines how they interact with the currently incumbent-led technological paradigm. We proceed along two analytical dimensions. First, we explore the materiality and mode of deployment of technological change, distinguishing between embodied and disembodied innovations, as proposed in the agricultural economics literature by Sunding and Zilberman (2001) and Dosi et al. (2021). Simply put, embodied innovations are those that are integrated into physical capital or machinery (i.e., technologies whose adoption requires investment in tangible equipment). Embodied digital tools are incorporated into physical agricultural equipment, such as selective-spraying modules, drones for crop monitoring, variable-rate technologies, and animal-based devices (e.g., ruminal boluses that track internal health indicators). These technologies often require capital investment and technical know-how for operation (Birner et al., 2021; van der Velden et al., 2024).

Disembodied innovations, on the other hand, refer more to software and information technologies and do not depend exclusively on physical devices, being relatively placeless. These technologies could be implemented without significant changes to capital goods and can be deployed without necessarily being tied to a particular machine or location (although they may require physical devices like computers or smartphones to work). These types of disembodied innovations include tools such as cloud-based advisory platforms, farm management apps, weather and pest forecasting systems, and data analytics services that support informed decision-making.

However, this distinction between embodied and disembodied innovations is insufficient to analyze the solutions provided by start-ups comprehensively. Several authors (Birner et al., 2021; Lavarello et al., 2019) emphasize the importance of classifying solutions according to their relationship with existing products and services, reflecting the functional integration type. Lavarello et al. (2019) argue that, unlike previous technological revolutions characterized by technological substitution and the entry of new players, DA is associated with leveraging complementarities between new enabling technologies and existing technological trajectories. Birner et al. (2021) suggest that product substitutability in DA can be seen as a factor that reduces market concentration, as substitutes tend to foster the entry of new players and competition. Therefore, this analysis incorporates a second fundamental dimension that distinguishes between substitute and complementary goods. Substitute goods can lower entry barriers and stimulate competition by enabling the replacement of traditional technologies (e.g., a spraying drone replacing a conventional sprayer). On the other hand, complementary goods may eventually strengthen the position of dominant market players by optimizing existing technologies and reinforcing dependence on established infrastructures (i.e., IoT sensors that enhance the efficiency of traditional irrigation systems) (Besanko et al., 2012).

A synthesis of our bi-dimensional conceptual framework is shown in Figure 1. This framework considers (i) the distinction between embodied and disembodied innovations (materiality of the innovation) and (ii) the classification of goods into substitutes and complements (the functional integration of the innovation). The combination of these dimensions results in a matrix with four quadrants, providing an analytical tool to explore the transformative potential of these innovations on the concentration of agricultural input markets.

4. DATA AND METHODS

4.1. Database building

The first point in our analysis is to identify and systematize a comprehensive list of *agrifoodtech* start-ups in the country. We first start with this more comprehensive concept (which includes solutions at the farmer level as well as at the mid- and downstream segments), and we then narrow down to DA start-ups, which constitute the main objective of this paper. We have not found fully harmonized and updated databases that collect systematic information on *agrifoodtech* start-ups. For this purpose, we combined industry reports with a selection of public sources, including news, press releases, and websites, until a comprehensive database was established. We started collecting available information from previous research studies and surveys conducted between May and July 2022 (Soler et al., 2022) and between July and October 2023 (Navarro et al., 2024). We complemented this information using Crunchbase, a database

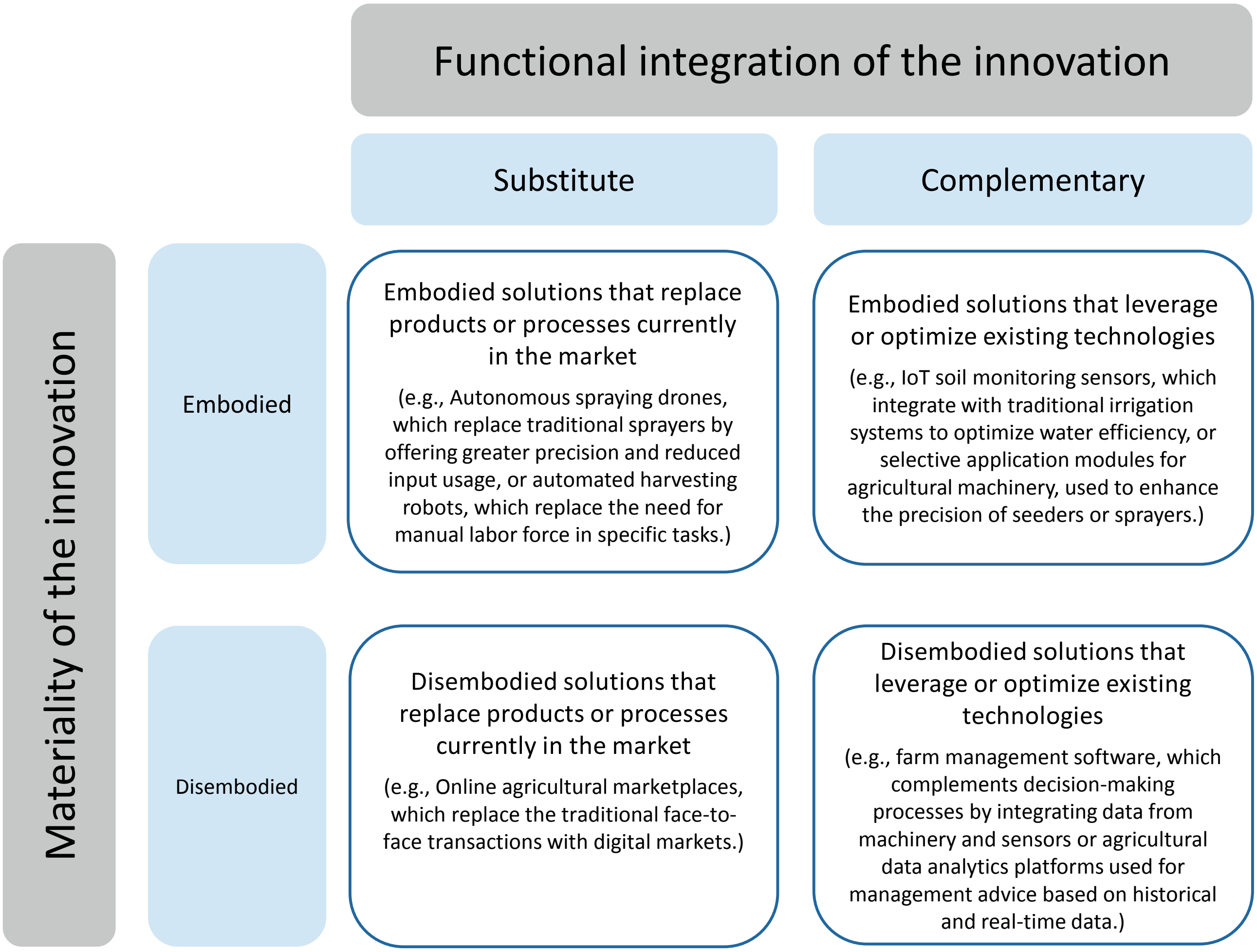

Figure 1. Categories of analysis. Classification of start-ups. Source: Own elaboration based on Sunding and Zilberman (2001), Lavarello et al. (2019), and Birner et al. (2021).

of innovative ventures increasingly used for academic research (Dalle et al., 2017). This information was also combined with ad hoc web searches and consultations with experts and stakeholders in the local entrepreneurial ecosystem.

While the term "start-up" lacks a universally accepted definition (Connolly et al., 2018; Klerkx & Villalobos, 2024), for this study, we define start-ups as business ventures characterized by two key elements: (a) an innovative approach underpinned by intensive research and development activities; and (b) scalability potential, reflected in business models which tend to be replicable across multiple markets and the promise of exponential growth for investors (Escartín et al., 2020; Vergara & Barrett, 2025). For instrumental purposes, we define Argentine *agrifoodtech* start-ups as companies founded and operating in Argentina that develop technologies in agriculture and food and have achieved (or are close to) at least a minimum viable product by October 2024. While there is no undisputed temporal criterion for defining start-ups (i.e., companies not exceeding a certain number of years), we include in our analysis companies founded in 2010 or later, considering that it was in early 2010s when concepts like Climate-Smart Agriculture, Digital Agriculture, and Agriculture 4.0 began to gain systematic attention in the literature (Alam et al., 2023; FAO, 2010). We acknowledge this is a pragmatic operationalization, that combines the innovativeness profile, product readiness and year of foundation does not fully capture other relevant dimensions of a start-up company, such as the funding stage (whether the company has already received pre-seed or seed funding, or it is more advanced into series A, B, etc.), governance and ownership structure, or the realized scalability or internalization potencial. Thus, our criteria should not be read as a definitive taxonomy for selecting or identifying start-ups, but rather as a practical shorthand for building an initial database.

As a first step, and to ensure comprehensive coverage and consistency with previous studies, we adopted an inclusive classification encompassing companies developing both agricultural-specific innovations and those implementing improvements across the entire value chain, including processing, logistics, marketing, and traceability. This is why, in this stage, we use the broader *agrifoodtech* denomination and we later move to specific DA companies. Our systematic search methodology yielded a database of 239 Argentine *agrifoodtech* start-ups. For each company, we compiled data on their description, primary value proposition, and core technology applied. Around three-quarters of these companies initiated operations after 2016.

4.2. Identifying and classifying DA start-ups

As a second step, we leverage this database to identify start-ups offering farmer-centered solutions in the field of DA in the upstream segment. The literature provides various proposals to classify the solutions developed by start-ups working in agriculture and food (AgFunder, 2024; Herrero et al., 2020, 2021; Mac Clay et al., 2024; McFadden et al., 2023), but due to the dynamic nature of the sector, no typology has yet achieved universal adoption. To distinguish between start-ups that provide DA solutions and those that do not, we classify the start-ups according to the criteria proposed by Mac Clay et al. (2024), which adopt a comprehensive agri-food value chain approach[4], allowing us to capture those companies specifically providing DA solutions to farmers (rather than to mid- and downstream segments of the value chain). This preliminary step is essential to contextualize DA start-ups within the value chain, evaluate their relative significance and visibility compared to other solutions, and understand their role within the broader innovation landscape in Argentina's agri-food sector. For instrumental purposes, DA solutions are defined as those within the categories of "*Precision agriculture, smart farming, and agricultural robotics*" and *"Digital Agribusiness Marketplaces"*[5], as outlined by Mac Clay et al. (2024).

To further characterize the remaining start-ups operating in the DA field, we apply the typology presented by McFadden et al. (2023), which categorizes digital solutions into three groups: *(i) "Data and Data collection", (ii) "Decision Support" and (iii) "Equipment and input adjustment based on data"*. Examples in the first category include data obtained from yield monitoring equipment, sensors, and images captured by drones, aircraft, or satellites. Decision support tools include digital maps or other visualizations of georeferenced data, mobile applications, and other analytical tools that provide management recommendations. Technologies in the third category primarily include guidance systems, automatic steering, and variable-rate applicators. The purpose of this classification is not to perform a selection (as was done in the previous step), but to provide an initial characterization of DA start-ups, using a standard criterion commonly applied in various reports on the subject. Finally, we characterize the subgroup of DA start-ups based on their primary technological features, following the typology introduced in the previous section (Figure 1). This framework classifies DA start-ups into four distinguishable categories: (a) embodied and substitute, (b) embodied and complementary, (c) disembodied and substitute, and (d) disembodied and complementary. A summary of the categories is presented in Table 1.

Based on this final classification, which reflects key technological attributes, we hypothesize about the potential of these start-ups to challenge the dominant position of large multinational companies in the agricultural input segment of agri-food GVCs. Given the nascent nature of these start-ups and the technologies they offer, our analysis adopts an exploratory perspective. We outline ideas on how and to what extent each of the four groups of innovations identified in Figure 1 could drive changes in the industrial dynamics of highly concentrated input markets.

5. RESULTS: CHARACTERIZING ARGENTINE START-UPS

5.1. Initial identification of DA start-ups

In this section, we present the classification of the group of 239 *agrifoodtech* start-ups identified in Argentina. We begin by identifying the subset of DA solutions that constitutes the core of our analysis, based on the categories presented by Mac Clay et al. (2024) (the details of this classification are shown in Appendix 2). Within the upstream segment, *Precision agriculture, smart agriculture, and agricultural robotics solutions* account for 41% of the total companies. These start-ups

[4] This typology comprises eleven different solutions, categorized by their position in the value chain.

[5] The authors in this work consider a broader category, which is "*E-commerce and delivery solutions*". Within this category, the authors include both apps specifically related to farmers' digitalization, as well as other apps linked to food distribution to the final consumer (for example, delivery apps). This second group of solutions is unrelated to what we define as digital agriculture, so for practical purposes, we divide the category into two to specifically capture "*Digital Agribusiness Marketplaces*", and the rest we indicate as "*Other*".

Table 1. Technological classifications used in the analysis.

Mac Clay et al. (2024)	McFadden et al. (2023)	Own Conceptual Framework
Start-ups providing Digital Agriculture (DA) solutions (including *precision agriculture, smart farming, and farm robotics* and *digital agribusiness marketplaces*)	Data and Data Collection	Complementary & embodied
Other Solutions	Decision-Making Support	Complementary & disembodied
	Data-driven Equipment and Input Adjustments	Substitute & embodied
		Substitute & disembodied

focus on developing solutions such as real-time data collection, satellite images and drones, farm management software, precision livestock technologies, and digital advisory services. DA start-ups have the potential to transform agricultural input markets since the vast amount of data they generate can be utilized not only by farmers to optimize decisions but also by other start-ups to improve their technologies. At the same time, there is a group of companies defined as *Digital Agribusiness Marketplaces* (7% of the total number of companies) which contribute to farmers' digitalization by connecting them with input suppliers and clients, and providing services related to price discovery. These two groups form the core of what is defined, for the purpose of this paper, as DA. As the analysis shows, around half of start-up companies in Argentina are oriented toward the upstream segment, providing digital services for farms. A possible explanation for this is related to the distinct agricultural profile of the country and the importance of primary production both for the internal productive structure and the export markets (World Bank, 2024).

From this first classification step, we retain 114 companies from the initial set of 239, which constitute our DA group (the full list of these companies is presented in Appendix 3). We will now focus on this subset of DA start-ups, which are the main object of this paper. As a first characterization, we apply McFadden et al. (2023) classification typology. As shown in Figure 2, we see a predominance in the categories of *Data and data collection* (37.7%)[6] and *Decision-making support*[7] (56.1%). This reflects a focus on solutions that are primarily oriented towards collecting information and optimizing the decision-making process. Technologies related to data collection and decision support are among the most adopted by Argentine farmers. According to Borbiconi et al. (Borbiconi et al., 2024), half of the farmers in Argentina use technologies that facilitate data collection. Puntel et al. (2022) note that remote sensing and mapping solutions have an adoption rate of between 60% and 80%. The *Data-driven Equipment and Input Adjustments*[8] category accounts for only 6.1%, indicating a lower representation of these solutions, which are more related to farming automation. This is also in line with adoption data. For equipment and inputs, registered rate adoptions are lower among Argentine farmers (except possibly for GPS, which is adopted mainly due to its integration into machinery). Variable-rate technology adoption ranges between 30% and 40% (Borbiconi et al., 2024; McKingsey & Company, 2024; Puntel et al., 2022).

5.2. Characterization of DA start-ups according to their technological features

After mapping and characterizing DA start-ups' profiles based on McFadden et al. (2023), we categorize them now using our own analytical framework, outlined in Figure 1. As a starting point, and based on the value proposition of the 114 start-ups that constitute our object of study, we list the specific solutions these companies are providing and label them in terms of both dimensions: the materiality and the functional integration of the innovation. This is presented in detail in Table 2. In each row, we explain the criteria behind classifying a solution as embodied or disembodied (materiality) and as complementary or substitute (functionality). For example, a farm digital advisory platform is disembodied in nature, as it does not require dedicated hardware (beyond a computer or smartphone), but is complementary, as it integrates data from different sources. On the other hand, a spraying drone is embodied, considering that these are physical devices equipped with sensors, spraying systems, and

[6] Examples of companies in this category are *Aseagro, Caburé, Control Campo, Nandi; Vistaguay or Pastech.*

[7] Examples of companies in this category are *Albor, Auravant, Eiwa or Sima.*

[8] Examples: *Deepagro, Campo Preciso, UCO Drone or Agrovants.*

Table 2. Classification of start-ups (materiality and functional integration) according to the main solution they provide.

Solution	Materiality	Functional integration	Start-ups
Custom tech solutions	Disembodied: These are software-based and digital developments without a dedicated physical component, focusing on data, analytics, and management.	Complementary: They enhance existing agricultural processes by digitizing, optimizing, and integrating operations rather than replacing them.	Agrosty, AgroToolbox, Integra Labs, Kan Territory Magoya, Sendevo
Digital agribusiness marketplaces	Disembodied: Software-based platforms without a dedicated physical hardware component. They operate online and are accessible via computers or mobile devices, meaning their value lies in the digital services they provide.	Substitute: These platforms replace traditional, in-person agricultural buying and selling channels by enabling producers and buyers to transact entirely online.	AgriRed, Agro24, Agrofy, Bipolos, Enbaca, Flashagro, GenGanar, HaciendaGo, La Rotonda, Malevo, Mercado Agrario, Modo Agrario, Muu Mercado Digital Ganadero, Pacta, Qira, Rastro Agropecuario, Wymaq
Digital platforms enabling sustainable and regenerative agriculture	Disembodied: Operate through digital platforms and services without physical hardware.	Complementary: Support sustainability and traceability by providing data and validation tools, improving decision-making rather than replacing production processes.	Cacta, Edra, Eirú, Puma, Ruuts, Ucrop.it
Farm digital advisory platform	Disembodied: Software and apps that process agricultural data via digital channels, without requiring dedicated hardware.	Complementary: Support and improve farming decisions by integrating data from other technologies, enhancing efficiency without replacing existing practices.	Agroapp, AgroBrowser, Agroconsultas, Agrohub, Agrology, Agro Aprilis, Avansys, Bold, Bright Data Analytics, Caburé, CROPilot.tech, Dymaxion Labs, EcoDrip, Eiwa, Fauno, iAgro, Kilimo, Kuna, Nutrixya, OKARATech, PreSeeds, Rastros, Satellites On Fire, Terratio, UrsulaGIS, Vistaguay, Yield Data
Farm Management Software	Disembodied: Digital applications that collect, process, and analyze agricultural data for farm management. It operates entirely through computers, tablets, or smartphones, without requiring a dedicated physical hardware component to function.	Complementary: These software enhance decision-making, optimize resource allocation, and improve efficiency in farm operations. It complements existing processes, machinery, labor, and agronomic practices by providing better coordination and data-driven management tools.	AgroPro, Auravant, Culti, Hi-Terra, Inteliagro, Lievrex, Ñandú, Riante, SaiLO, Sima, SmallData
Livestock digital advisory platforms	Disembodied: Software and digital platforms accessible via computers or mobile devices.	Complementary: Provide management support and advisory tools that optimize livestock production without substituting existing practices.	Nandi, RumIA, Uniagro soft
Livestock identification with AI	Disembodied: Based on software and AI vision systems, not dependent on physical devices.	Substitute: Replaces traditional identification methods (tags, marks) with digital recognition powered by artificial intelligence.	IDanimal
Livestock management software	Disembodied: Digital systems and applications that collect, process, and analyze data for livestock management without tangible hardware.	Complementary: Strengthen livestock production by enabling traceability, data-driven management, and efficiency, without replacing existing practices.	Avismart, Cattler, Cowdoo (Raíces), FieldData, Finca

(Continued)

Table 2. (Continued).

Solution	Materiality	Functional integration	Start-ups
Real-time monitoring of air quality with sensors	**Embodied:** Requires physical sensor devices installed in the environment.	**Complementary:** Provide environmental data that improves management and risk prevention, supporting agricultural operations rather than replacing them.	AR-PUF, Indegap
Real-time monitoring of climate with weather stations	**Embodied:** Weather stations are tangible devices capturing and transmitting data.	**Complementary:** Offer real-time climatic information that supports planning and decision-making without replacing production processes.	AgroTrack, Canopilogger, Climate Sense, MKL Agro, Mixon, Pampe.ro, Smartium
Real-time monitoring of fodder with satellites	**Disembodied:** Service based on satellite imagery and data analytics, delivered digitally without requiring specific hardware.	**Complementary:** Improve fodder management by providing objective and continuous information without substituting production.	Forrager
Real-time monitoring of grass with sensors and satellites	**Embodied:** Combine sensors and smart devices installed in the field with satellite data.	**Complementary:** Optimize pasture management by supplying precise and integrated information, enhancing existing practices.	Pastech
Real-time monitoring of livestock water systems with sensors	**Embodied:** Depend on physical devices and sensors installed in water systems.	**Complementary:** Strengthen existing infrastructure by enabling monitoring, alerts, and efficient use of resources.	Agrocheck, Control Campo
Real-time monitoring of machinery with sensors	**Embodied:** Sensors and hardware integrated into agricultural machinery.	**Complementary:** Improve existing equipment with real-time traceability, control, and efficiency, without replacing the machinery itself.	Acronex, Minnow, Corvus (AGDP), DVL Satelital
Real-time monitoring of silobags with sensors	**Embodied:** Physical sensors placed in silobags to track storage conditions.	**Complementary:** Support and enhance storage systems by providing data to prevent losses and improve conservation.	Wiagro
Real-time monitoring of soil with sensors	**Embodied:** Depend on physical sensors installed in the soil.	**Complementary:** Complement agronomic practices with real-time data on nutrients, humidity, and soil conditions.	Agrosense, Briste, Clarion
Real-time monitoring of water systems with sensors	**Embodied:** Requires physical devices and automation systems in irrigation or water infrastructure.	**Complementary:** Add control, efficiency, and automation to water systems, without substituting the infrastructure itself.	Hidromotic Ingeniería, Ponce
Smart devices and robotics for livestock	**Embodied:** Physical devices and robotic systems applied to livestock management.	**Complementary:** Enhance animal husbandry with monitoring, automation, and precision management, while keeping traditional production practices.	Bastó, Cattle Trace (Onsen Ingeniería), Dale Vaquita, Digirodeo, El Ojo del Amo, Huella Software, Magno, Novimetrics
Smart devices for sprayers	**Embodied:** Physical devices integrated into spraying machinery.	**Complementary:** Improve precision and reduce input use by optimizing existing sprayers rather than replacing them.	DeepAgro
Solutions for smart data and connected devices	**Disembodied:** Provide digital platforms and connectivity (e.g., satellite data, IoT integration) without field hardware.	**Complementary:** Strengthen agricultural systems by enabling communication, data access, and interoperability of devices.	Innova Space, Satellogic, Vertrev

(Continued)

Table 2. (Continued).

Solution	Materiality	Functional integration	Start-ups
Spraying drones	**Embodied:** Physical devices equipped with sensors, spraying systems, and autonomous navigation technology. Their operation depends on the physical machinery itself.	**Substitute:** They replace traditional spraying equipment, such as tractor-mounted sprayers, by performing the same task and reducing reliance on older machinery for spraying operations.	Agrovants, Servidrone, UCO Drone

Source: Own elaboration based on the two dimensions presented in Figure 1.

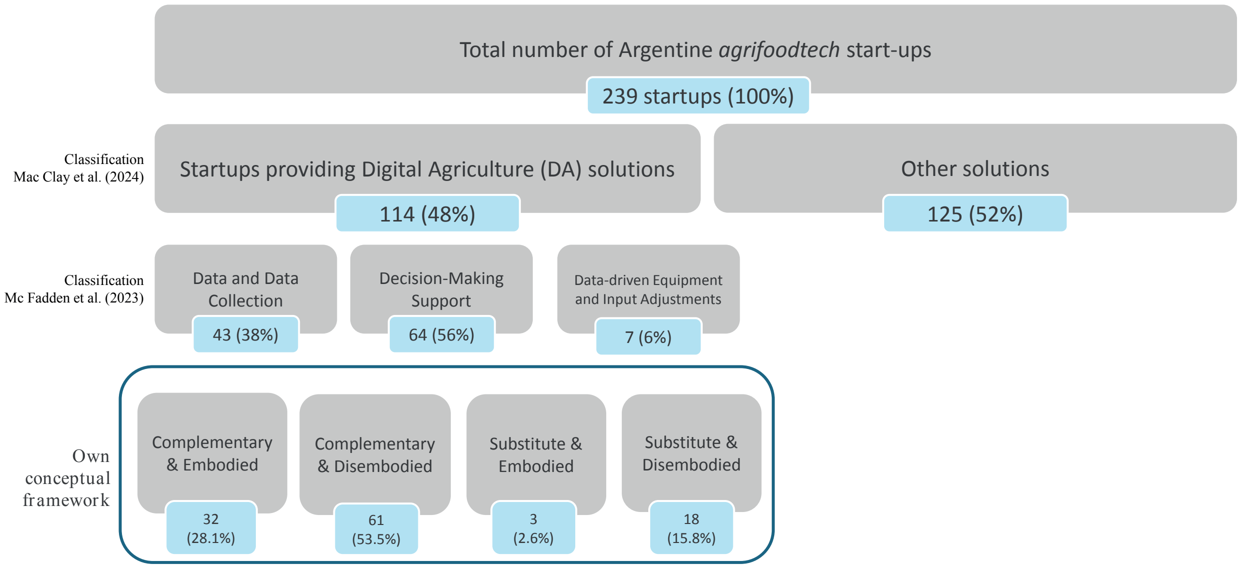

Figure 2. Summary of the classification and characterization process.

autonomous navigation technology, and are substitutes in their functional nature (as they cover the same function as traditional spraying equipment).

When we examine this analysis as a whole, the first point to highlight is that Argentine digital agriculture start-ups notably gravitate towards complementary solutions, that enhance the efficiency of existing technology platforms without replacing current production tools. As shown by Figure 2, among the 114 digital agriculture start-ups, approximately 80% offer complementary solutions. In the group of embodied complementary solutions (28.1% of total companies), we find devices for soil monitoring, precision irrigation systems, and technologies to optimize agricultural input requirements. One example is DeepAgro, which offers a device (called sprAI) that enhances the spraying process through an AI-based system capable of weed recognition, enabling more efficient use of machinery. They have recently incorporated a large language model system that enables better task tracking and facilitates inquiries regarding equipment efficiency (Martínez, 2025). The recent partnership between DeepAgro and a local agricultural machinery manufacturer illustrates the complementary nature of this solution (La Nación Campo, 2024). Other examples include cases like Cattler or Digirodeo, which offer smart devices for livestock management, Wiagro, which provides sensors for monitoring silobags or Agrosense, offering devices for soil monitoring.

A second group (53.5% of the companies in DA) provides disembodied complementary solutions, such as digital farm management tools and data analysis platforms. This category includes software companies such as Eiwa, Agrology, or iAgro, which help farmers integrate data collected from their agricultural machinery, telemetry systems, geographic information systems, and accounting software. The goal is to support more efficient farm management and data-driven decision-making. These tools offer a more precise and integrated visualization of information, and in some cases, provide management recommendations based on data analysis. However, they are complementary solutions in the sense that, despite the value they offer, they still rely on the generation of primary data from other equipment or software. Some firms in this category are even forming alliances with telecommunications companies to ensure connectivity in the field, which is crucial for data collection and the integration of cloud-based equipment (Vazquez, 2024).

Conversely, substitute solutions, which replace entirely current products, processes, or tools, are marginal within the DA landscape in Argentina. Only 2.6% of DA companies correspond to embodied substitutes. We can mention the case of companies such as UCO Drone, Servidrone, and Agrovants, which offer drones for crop spraying services. This practice helps avoid losses caused by crop or soil damage resulting from ground-based equipment, while also allowing spraying in areas that are otherwise inaccessible and achieving greater overall precision. With improvements in the load capacity of drones (from approximately 10 liters to nearly 50 liters, increasing efficiency by hectares per hour), many farmers in Argentina are beginning to replace some ground-based applications with drones (Razzetti, 2025). However, this trend is still in its early stages.

Finally, among the group of companies offering disembodied substitute solutions (15.8% of total), we find agricultural marketplaces, such as Agrofy or Agrired, which facilitate both the purchase of inputs (such as crop protection products and fertilizers) and even the sale of agricultural production. These marketplaces aim to disintermediate the value chain by enabling farmers to bypass traditional local distributors and purchase directly. Although still in its early stages, this trend clearly shows potential to substitute the conventional channels. In Argentina, only about 20% of farmers regularly purchase online, although those who have done so express an intention to continue using the online channel (Borbiconi et al., 2024).

6. DISCUSSION: CAN DA START-UPS CHANGE INDUSTRIAL DYNAMICS IN THE AG-INPUT MARKETS?

As outlined in the conceptual framework, the interactions between incumbents and start-ups in the context of technological change can have multiple facets, allowing more flexibility to technological exploration and enabling open innovation and deeper inter-firm linkages. This analysis focuses specifically on whether the technological profile of DA start-ups provides a sufficient foundation for transforming existing market dynamics, challenging the market positions of established dominant firms. Drawing on our previous classification of DA start-ups in Argentina in Section 5, we propose an exploratory and conceptual analysis to examine whether the technological characteristics of these start-ups possess transformative potential for the industrial organization of agricultural input markets, or whether they will reinforce the market power dynamics that have prevailed in the sector over the past thirty years (as described in Section 2). Given the current lack of sufficient empirical evidence on this topic, the ideas presented in this analysis should be regarded as an exploratory exercise.

At first glance, the predominance of complementary solutions and the low representation of substitute technologies appear to limit their capacity to disrupt the current balance of power. Large companies can preemptively acquire start-ups, integrating innovative technologies while maintaining market dominance. Furthermore, start-ups developing complementary technologies, whether embodied or disembodied, often depend on the infrastructure, data, or distribution channels of large companies, which limits their independence and ultimately strengthens the position of the incumbents.

Dominant multinational companies are leveraging complementary technologies to transition from input-based business models to platform or solution-based models. For example, a crop protection company that previously offered herbicides or pesticides is now offering systemic and integrated solutions to achieve weed and pesticide-free farms, thereby minimizing the need for agrochemicals. While greater precision in product application could be a driver of a sales reduction of these companies' core products, digital tools enable companies to integrate solutions and shift their value creation model. This transition offers comprehensive agronomic management solutions that complement traditional product sales. Another example could be the case of an agricultural machinery company, which in the past obtained revenue mainly from the sale of products (i.e., tractors) and today seeks to offer a service of real-time data analysis of the field to maximize the efficiency of the planting process. In both cases, companies leverage smart technologies to transform product sales into recurring service or subscription revenue streams.

Conversely, substitute solutions may represent a more evident opportunity to generate a disruptive market impact. The development of substitute solutions, such as autonomous machinery, could facilitate the entry of new players, breaking the entry barriers imposed by large companies and diversifying the agricultural input market. However, their low representation among Argentinian start-ups suggests the existence of significant entry barriers, including prohibitive scaling expenses, limited access to capital, and challenges in establishing and managing physical infrastructure. Aware of the threat posed by these specific innovations, large companies may adopt defensive strategies to safeguard their leadership position and neutralize the impact of innovations that could challenge their value propositions.

Our analysis is in line with previous evidence on the topic. Lavarello et al. (2019) observe that digital technologies tend to reinforce existing technological trajectories rather than disrupt them. Sauvagerd et al. (2024) show that despite many new digital solutions coming from small companies, the strategies of large incumbents tend to consolidate an oligopolistic landscape in these new platforms. Mac Clay et al. (2024) show that incumbent firms in the agricultural machinery, seed, and crop protection fields are employing corporate venture strategies to invest in digital agriculture platforms that may allow an upgrade in their own services and operations. In fact, these corporate venture strategies show that even when incumbent firms develop their own digital branches, they still seek complementarities in solutions developed by start-ups. There are several examples in this line, such as BASF and Yara investing in Ecorobotix[9], a company utilizing AI for autonomous crop protection, Syngenta investing in Greeneye[10], an AI-driven precision spraying solution, or Bayer investing in EarthOptics[11], a precision agriculture company focused on soil health, to mention a few. The rapid acceleration of technological innovation and the proliferation of digital solutions have led to a fragmented landscape, making it virtually impossible for any single firm to develop all the necessary capabilities internally. This has led to the need for external exploration of complementary capabilities. In a similar line, Rotz et al. (2019), Hackfort (2021), and Clapp and Ruder (2020) explain the political economy behind the development of digital solutions and how multinational companies tend to prioritize the development of technological lines that are aligned with their own interests and may lead them to higher benefit capture.

Additionally, the type of innovations developed by DA start-ups, whether embodied or disembodied, also influences their potential to disrupt concentration in the agricultural input industry. While embodied solutions directly impact agricultural production, their ability to alter concentration dynamics is limited. The "physical" nature of these innovations requires scale, production processes, physical infrastructure – and consequently capital – as well as the necessary channels to distribute these products, all of which constitute a set of entry barriers for smaller firms. In contrast, disembodied solutions offer a different field of action with greater potential to disrupt industrial concentration dynamics. These technologies enable greater flexibility in terms of scalability and accessibility, as start-ups could offer their solutions to a wide variety of actors, providing them with a potentially global reach.

A key element in this discussion is technological compatibility. Birner et al. (2021) state that interoperability between various digital tools and agricultural machinery can influence market concentration. If start-ups develop technologies that are not compatible with the dominant systems, they may face difficulties in scaling up and attracting users. Conversely, promoting standards that ensure interoperability could reduce entry barriers but also reinforce the dominant position of large companies, that hold a first-mover advantage in terms of the existing technological infrastructure. Finally, access to information and the use of big data emerge as additional factors that may strengthen concentration dynamics. This raises questions related to the ownership and governance of such data. Digital technologies generate vast amounts of data, which, if exclusively controlled by large agricultural input companies, could further consolidate their advantages by optimizing processes, reducing costs, and adjusting prices.

As a final point in this section, we mention a caveat to our analysis. While we have focused exclusively on the technological characteristics of the solutions offered by start-ups, other factors may help reshape market dynamics. Further factors also require careful consideration, especially given the complex nature of the problem we are studying, such as incumbent firms' strategies and business reactions, access to venture capital (which shapes start-up scaling potential), and regulatory frameworks that influence value chain dynamics from producer to consumer.

7. CONCLUSIONS

This paper provides a preliminary assessment of the potential of DA start-ups to transform market dynamics in the agricultural input segment of agri-food GVCs, challenging dominant firms' current positions as industry leaders. For this purpose, we have characterized the technological features of 114 DA start-ups in Argentina (a country with increasing momentum in start-up creation),

[9] https://press.ecorobotix.com/238233-ecorobotix-raises-52m-in-new-funding
[10] https://www.syngentagroupventures.com/news/news-release/greeneye-technology-raises-funding-round-22m
[11] https://earthoptics.com/news-insights/earthoptics-secures-27-6-million-series-b-funding

based on two technological dimensions (embodied/disembodied technologies and complementary/substitutive). Our analysis reveals that most Argentine start-ups offer complementary solutions to existing technological packages. They enhance and optimize the production tools already available to farmers but are unlikely to replace them. This, in turn, presents an opportunity for dominant firms to integrate these technologies into their own innovation pipelines (through start-up acquisitions, strategic alliances, or investments via corporate venture capital), thus reinforcing the oligopolistic dynamics that have shaped the sector over the past 30 years. In this sense, despite the promise that start-ups bring to the market through new technologies, our preliminary analysis suggests that their disruptive potential concerning the industrial dynamics of the agricultural input market remains somewhat limited.

Based on these findings, this study offers insights for various stakeholders. Large firms are compelled to develop open innovation capabilities. Collaboration with external actors becomes imperative to leverage the potential of new technologies and maintain competitiveness in a globalized and dynamic market. At the same time, ICTs have lowered the barriers to entry in agri-food markets, enabling new players to introduce digital innovations. Meanwhile, start-ups need to acknowledge that generating solutions and innovations is a process distinct from scaling, commercializing, and distributing these solutions in the market – a domain still dominated by large firms.

The above discussion underscores that start-ups alone do not appear sufficient to reverse industry concentration in agri-food agricultural input markets. This scenario demands innovative public policies that foster a more inclusive environment, combining public investment in R&D with regulatory frameworks to mitigate concentration risks. Additionally, measures are needed to facilitate technological interoperability, and address the infrastructure and financing challenges that start-ups face in order to enhance their competitiveness.

This study represents a preliminary effort to explore the role of DA start-ups in the transformation market dynamics, adopting a prospective viewpoint, which is suitable given the early and rapidly evolving stage of innovation in agriculture. As such, rather than offering conclusive impact assessments, we aimed to map out emerging trends and highlight possible directions of change in market dynamics and value chain morphology. Our work, exploratory in nature, reflects the novelty of the DA field, which implies limitations in the availability of longitudinal data. Our findings provide a foundation for future research, particularly as more empirical evidence becomes available. Dynamics such as investments, acquisitions, mergers, and strategic alliances would be valuable avenues of exploration. At the same time, it is necessary to intensify efforts to promote systematization and ensure the public availability of market data, sales figures, and market shares. This would enable the development of studies with a more quantitative focus. Additionally, examining the dynamic evolution of the market and incorporating factors such as regulations, public policies, and the adoption of technology by farmers would open new perspectives on better understanding the forces shaping the structure of this ever-changing sector and achieving a more comprehensive understanding of the phenomenon.

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Editorial

3 Giulia Maesano, Davide Menozzi, Davide Viaggi, *Economic and policy analysis of technology uptake for the smart management of agricultural systems*

Full Research Articles

9 Alexander Kühnemund, Guido Recke, *Intention to use AI-Based Camera Systems in German Pig Farming: An extended technology acceptance model*

29 Elena Cozzi, Davide Menozzi, Giulia Maesano, Maurizio Canavari, Cristina Mora, *Digital technology adoption among italian farmers: An extended technology acceptance model approach in the horticultural sector*

45 Maria Sabbagh, Luciano Gutierrez, *Farmers' intention to use Agriculture 4.0 in marginal and non-marginal conditions*

67 Giuseppe Timpanaro, Giulio Cascone, Vera Teresa Foti, *Enabling technologies in citrus farming: A living lab approach to agroecology and sustainable water resource management*

85 Giulia Maesano, Seyyedehsara Sadrmousavigargari, Alessandra Castellini, *Consumer intentions to purchase organic pasta with blockchain-based traceability*

101 Cosimo Pacciani, Eleonora Catellani, Andrea Bacchetti, Chiara Corbo, Federica Ciccullo, Marco Ardolino, *Agriculture 4.0: Technological adoption, drivers, benefits and challenges in Italy. A descriptive survey*

121 Ahmed Moussaoui, Rino Ghelfi, Davide Viaggi, *Agritech policy landscape: Insights from relevant stakeholders on policy issues and strategic plans in Italy*

135 Julián Arraigada, Pablo Mac Clay, *The potential of digital agriculture start-ups to reshape market dynamics in the ag-input industry: A case study from Argentina*