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Reinventing French Agriculture: The Era of Farmers 4.0, Technological Innovation and Sustainability

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Abstract:

As digital transformation accelerates across the agricultural sector, understanding farmers' adoption behavior becomes critical to facilitating sustainability and innovation. This study investigates the behavioral, contextual, and economic factors that influence French farmers' adoption of innovative agricultural technologies. Using a mixed-methods approach, we first conducted qualitative interviews to explore resistance to innovation. Based on these insights, we refocused the quantitative phase on technology adopters to examine the factors that lead to usage.

We propose the French Farming Innovation Adoption (FFIA) model, an agricultural adaptation of the UTAUT2 model. The model incorporates domain-specific constructs including Perceived Sustainability Advantages and Price Value. Data from 171 farmers were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that original UTAUT2 variables—Performance Expectancy, Facilitating Conditions, and Social Influence—do not directly predict Technology Utilization, but rather operate indirectly through Price Value. Price Value also mediates the influence of Social Influence on Perceived Sustainability Advantages.

These findings contribute to Information Systems literature by demonstrating how economic perception mediates behavioral drivers in digital innovation contexts, particularly in cost-sensitive sectors like agriculture. Practical implications emphasize designing support mechanisms and communication strategies that align sustainability and innovation with farmers' perceived economic value.

Keywords: Farmers 4.0, Artificial Intelligence, Government Subsidies, Innovative Technologies, Sustainability, Utaut2, Technology Adoption.

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1 Introduction

The agricultural sector is undergoing a significant transformation driven by the adoption of advanced technologies. Innovative agriculture, which incorporates Internet of Things (IoT), devices, drones, artificial intelligence (Lakshmi & Corbett, 2023; Harfouche et al., 2019), and precision farming tools, offers promising solutions to address key challenges such as resource optimization, environmental sustainability, and increased productivity (Thomas et al., 2023; Karunathilake et al., 2023; Muhammed et al., 2024). Data-driven interventions are enabled through real-time monitoring of environmental factors, soil conditions, and crop health, made possible by IoT devices and sensors (Taheri et al., 2022; Dobre et al., 2024). High-resolution aerial imaging from drones and unmanned aerial vehicles (UAVs) supports targeted activities like precision watering and pest management, providing valuable insights about crop conditions (Dash et al., 2024). These advances have demonstrated significant benefits, such as increased productivity, reduced environmental impact, and optimal resource use (Tyagi et al., 2024; Haapala et al., 2024). The following factors motivate climate-smart practices (Pedersen et al., 2024): i) adoption driven by the aim to mitigate climate change effects by lowering pesticide and water use; ii) multi-stakeholder initiatives are essential for aligning technologies with farmers' capacities and market needs.

France faces unique challenges in implementing these innovative technologies. The Common Agricultural Policy (CAP) and the Mercosur Agreement are causing a crisis in the agricultural sector because they aim to implement new ethical laws related to sustainability. They support shifting towards a resilient, sustainable, intelligent agriculture industry (Kritikos, 2017), and they play a crucial role in providing support and resources for the transition to smart agriculture (Ministère de l'Agriculture et de la Souveraineté Alimentaire, 2020). Similarly, in Europe, agriculture is struggling due to the interaction between the Mercosur Agreement and the European Union's Common Agricultural Policy (CAP). CAP has implemented changes that align with the European Green Deal and Farm to Fork Strategy to support farmers, ensure food security, and promote sustainable practices. The primary objectives of these reforms are to preserve biodiversity, promote organic agriculture, and reduce pesticide use. However, for farmers—especially smallholders—who struggle to compete in international markets, these sustainability goals frequently result in higher production costs and administrative issues (Cuadros-Casanova et al., 2023; Farm Europe, 2024). At the same time, low-cost agricultural imports, such as beef and soybeans, are made easier to access EU markets through the Mercosur Agreement, which aims to promote trade between the EU and Mercosur nations. EU farmers who follow the stricter CAP restrictions face unfair competition from these imports, which are often produced under less challenging environmental and animal welfare standards (Abis, 2024). Additionally, the expansion of agriculture in Mercosur countries is linked to deforestation and biodiversity loss, posing a challenge to the EU's sustainability ambitions (Burrell, 2009).

Economic anxiety and farmers' call for policy changes have resulted from the combined pressure of Mercosur imports and CAP reforms (2023–2027). The EU's Green Deal has also drawn criticism for failing to support farms in their transition to sustainable practices (Intelligence, 2024). Strengthening trade security measures, supporting small farmers, balancing welfare and environmental protection, and successfully promoting EU agricultural products as high-quality, sustainable substitutes are all crucial to resolving these problems. These measures are essential to preserve the resilience of the farming actors while striking a balance between global trade and environmental objectives.

In the field of smart agriculture, adoption studies have taken contextual and psychological variables into account. To assess farmers' adoption of automated irrigation technologies, Lee and Kim (2024) expanded UTAUT2 (Venkatesh et al., 2003) by incorporating perceived risk and individual inventiveness. This highlights the fact that behavioral and attitudinal factors, in addition to performance expectations, influence adoption decisions. The study by da Silveira et al. (2023) examined farmers' opinions on the constraints preventing the deployment of Agriculture 4.0 and found that the primary ones are still infrastructure deficiencies, complexity, and concerns about cost. The way perceptions of sustainability benefits affect adoption decisions has received less attention, despite this research providing insight into risk perceptions and barriers. This gap is relevant in the French agricultural sector, where sustainability is at the center of public discussions and policy frameworks such as the Farm to Fork plan and CAP changes (European Commission, 2020).

This paper examines the interplay between factors that may affect technology adoption, perceived sustainability, and price value, drawing on re[22]cent advancements in innovative technologies and theoretical frameworks that analyze technology acceptance and innovation resistance (Pivoto et al., 2019). It presents innovative agricultural implementations in France and identifies solutions to overcome barriers that limit their adoption. Ultimately, this study contributes to the ongoing debate about sustainable agricultural methods and the potential impact of digital innovation on the future of agriculture.

All the points mentioned above lead us to the following research questions:

RQ1: What factors influence the adoption of innovative technologies by French farmers?

RQ2: Does the perception of sustainability affect French farmers' adoption of innovative technologies?

To address these questions, our study aims to gain a deeper understanding of the factors that influence French farmers’ adoption of innovative agricultural technologies in the context of current financial and regulatory challenges. Accordingly, we explore both the motivations and barriers that shape adoption decisions, as well as the role that perceptions of sustainability have in either promoting or resisting the adoption of these innovations.

The paper is divided into four different sections: i) the first section is the literature review, which discusses the integration of advanced technologies and defines the various concepts used in our model. ii) The second section describes the methods used, which are both qualitative and quantitative. We employed a qualitative methodology to gain a deeper understanding of the resistance to technology adoption among some farmers, and we adopted a quantitative method to better understand the adoption of technologies and their relationship with sustainable practices among French farmers. iii) the third section presents the results and data analysis, and iv) the fourth section is dedicated to discussing the results and explaining the study's theoretical and practical contributions and limitations.

2 Literature Review

2.1 Technological Integration and Sustainability in Smart Agriculture

The development of agricultural practices can be divided into different stages. Agriculture 1.0 refers to early, conventional farming techniques that focused on subsistence farming, characterized by limited technological access, reliance on human labor, animal power, and simple equipment (Assimakopoulos et al., 2024). During the Industrial Revolution, mechanization and chemical inputs were introduced in agriculture, leading to Agriculture 2.0, which significantly increased yields but raised concerns about environmental deterioration (Dash et al., 2024). Precision agriculture emerged with the digitalization age of Agriculture 3.0, integrating early computer systems, GPS, and automated tools (Dubois et al., 2019; Ahmed et al., 2024; Monteiro et al., 2021; Dhaigude & Ghosh, 2023; Getahun et al., 2024). Advanced digital technologies, such as IoT and sensors, enable real-time monitoring of soil conditions and crop health, facilitating data-driven decision-making (Dobre et al., 2024; Parashar et al., 2024). Big data and AI are also incorporated into the agriculture 4.0 phase to enable data-driven, sustainable development (Shoormann et al., 2023; Klerkx & Rose, 2020) and farming systems (Rane et al., 2024; da Silveira et al., 2023; Balkrishna et al., 2023). In addition, Unmanned Aerial Vehicles (UAVs) and drones are utilized for monitoring and aerial photography (Gupta et al., 2025). They allow specific responses while offering information about agricultural conditions (Dash et al., 2024). This evolution is expanded by the upcoming Agriculture 5.0 phase, which emphasizes sustainability and ethical practices while promoting human-technology partnership (Gyamfi et al., 2024). The widespread adoption and advancement of precision agriculture, supported by the digitalization of farming, are driving the development of numerous innovative approaches that integrate agronomic expertise and agroecological practices with innovative technologies (Reichardt et al., 2009; Saba et al., 2018; Getahun et al., 2024; Karunathilake et al., 2023).

These phases are facilitated by frameworks such as smart farming and precision agriculture, which maximize resource utilization through sophisticated monitoring. Additionally, concepts like climate-smart agriculture (Rodríguez-Barillas et al., 2024) and regenerative agriculture, which focus on resilience and ecological restoration (Pedersen et al., 2024; Mbanasor et al., 2024), are also employed. These stages illustrate how agriculture is adapting to meet environmental sustainability challenges and address global food security concerns (Tyagi et al., 2024; Haapala et al., 2024). In France, innovative solutions in the farming sector are increasingly recognized for their potential to enhance productivity and sustainability (Florez et al., 2021). These original concepts have replaced conventional farming practices and traditional linear theories (Saba et al., 2018) with more accurate and efficient alternatives. Meeting sustainable development goals and contributing to reducing the problems caused by the world's expanding population.

Researchers from the European Commission's Joint Research Centre (JRC), as well as Greece, China, and Spain, examined 239 international scientific publications to assess the impact of precision agriculture technologies on various environmental, economic, and human aspects. Their research shows precision agriculture has a huge potential to transform sustainable farming methods and crop security (Anastasiou et al., 2023). According to this study, up to 97% fewer herbicides and 70% fewer insecticides are used, improving the soil and water quality. Adopting technology is encouraged by economic advantages such as increased crop yields and reduced input costs.

Despite these benefits and advantages, several barriers keep these technologies from being extensively used. The high initial investment costs and need for professional skills present additional challenges for smallholder farmers, who often lack the infrastructure and resources to implement such solutions (Bontsa et al., 2023; Assimakopoulos et al., 2024). Government programs and financial incentives play a crucial role in mitigating these issues and facilitating the transition to smart agriculture (Haapala et al., 2024). Furthermore, government support in the form of subsidies and educational initiatives is essential for closing the gap between invention and real-world implementation (Chammaa, 2017; Anubhav et al., 2025). They are essential for encouraging innovation because they reduce financial barriers, support environmental sustainability, and guarantee food security (Akkaya et al., 2020). These subsidies encourage farmers to develop and embrace new technology by reducing risk, giving financial resources, and showing recognized acceptance (Wu et al., 2022).

Agronomic practices are greatly influenced by the perceived sustainability advantages of agricultural technology, such as AI-powered irrigation scheduling, precision nutrient application using drones, or Internet of Things-based soil moisture monitors. When these instruments are linked to long-term gains in ecosystem services, climate resilience, and resource efficiency, farmers are more likely to use them (Anastasiou et al., 2023; Dash et al., 2024).

The transition from intensive input-based systems to data-driven, input-optimized agronomic techniques is also supported by this perspective, which is a significant theme in the current literature on precision agronomy and climate-resilient cropping systems.

2.2 Theories of Technology Acceptance and Utilization

The adoption of innovative technologies by farmers is explained by several fundamental hypotheses in the context of smart agriculture. The Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975) offers an early behavioral framework, which postulates that attitudes toward the action and subjective norms influence people's intentions to engage in it, such as adopting new technology. This implies that a farmer's decision to employ technologies in agriculture is impacted by social (Yadav et al., 2023) pressures or expectations from peers, cooperatives, or policy stakeholders in addition to their assessment of the technology (e.g., its relevance or utility) (Jorgensen & Martin, 2015). Furthermore, the Technology Acceptance Model (TAM) (Davis, 1989) identifies perceived utility and perceived ease of use as two key factors influencing the adoption of technology. When innovative technologies are perceived to increase productivity, ease decision-making, or optimize supply chains in agricultural contexts, they are more likely to be embraced; this is especially true when the technologies are easy to use and require little training (Lee et al., 2024; Sood, 2024). Farmers can test these technologies (e.g., automated machinery, remote sensing systems) before implementing them on a large scale (Rogers, 2003), which also explains adoption patterns based on the relative advantages of innovations, their compatibility with current farming systems, and their trialability (Dash et al., 2024).

2.3 Applying the UTAUT Framework Across Sectors and in the Agricultural World

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) is a framework designed to predict technology acceptance in organizational contexts. It integrates the central constructs of eight earlier models of technology adoption, combining insights from human behavior and computer science to provide a comprehensive explanation of technology use. It offers insights into how social influence, performance expectancy, and facilitating conditions (such as training programs, infrastructure, and digital skills) impact the adoption of AI in agriculture (Otter, 2023; Ncube, 2023). When combined, these models offer a thorough framework for comprehending how farmers' technology adoption behaviors are influenced by the interaction of cognitive, social, and infrastructure factors in different fields like banking (Parthiban et al., 2024), Cybersecurity (Wallace et al, 2020), and health (Gopinath, 2022). Numerous studies have expanded the UTAUT2 framework by incorporating domain-specific constructs to better explain technology adoption. In the mHealth context, Zhang, Lou, and Wang (2022) extended UTAUT2 by integrating perceived disease threat and trust. In the field of mobile payments, Slade et al. (2015) incorporated perceived security, privacy, and trust, improving behavioral intention modeling in proximity mobile payment adoption. In healthcare robotics, Califf et al. (2023) proposed an extension of UTAUT2 by adding trust in technology and performance expectancy to explain users' acceptance of healthcare robots. While Chandra et al. (2010) developed and tested a trust-centric model for m-payment adoption, Arenas-Gaitán et al. (2023) extended UTAUT2 with epistemic value and perceived security to assess the adoption of mobile banking services in rural Spain. Finally, in the context of smart agriculture, Lee and Kim (2024) extended UTAUT2 with perceived risk and personal innovativeness to evaluate farmers' adoption of automated irrigation technologies. These widely cited studies provide a strong precedent for extending UTAUT2 with constructs such as sustainability perception and price value, as proposed in the FFIA model, to fit the agricultural innovation domain better.

UTAUT is widely utilized in agricultural technology adoption research because of its predictive ability. Beza et al. (2018), for example, adapted UTAUT to evaluate mobile-based extension services on smallholder farms in Ethiopia. They demonstrated that social influence and facilitating conditions were more important than performance expectancy in predicting farmers' uptake, underscoring the significance of infrastructure and contextual enablers. Applying UTAUT to conservation agricultural methods, Faridi et al. (2020) discovered that Iranian paddy farmers' adoption of water and soil conservation strategies is significantly influenced by their attitudes.

The adoption of conservation measures is also significantly influenced by behavioral, economic, social, and environmental factors. In contrast, Ronaghi and Forouharfar (2020) demonstrated that in smart agricultural settings, the intention to utilize IoT technology in a typical Middle Eastern country was positively influenced by performance expectancy, social influence, and facilitating conditions. When applied to agricultural innovations, these studies demonstrate the potential and limitations of the UTAUT model. While fundamental concepts like performance expectancy and facilitating conditions remain highly relevant, issues unique to agriculture, such as cost and infrastructure gaps, necessitate theoretical expansions. This synthesis highlights the need for further tailoring UTAUT to the farming environment in France, where adoption decisions may be influenced differentially by perceptions of sustainability and government support.

We now operationalize these findings into the main variables of our research model, building on the theoretical frameworks described in this part. We use UTAUT2 as a starting point and expand it with constructs specific to the agricultural sector. The variables and related hypotheses are presented as follows: ***Facilitating conditions*** **(Government subsidies)** are defined as the monetary and policy-based assistance governments offer to encourage the use of smart farming technologies. They act as an enabling factor, lowering operational and financial obstacles to the adoption of smart technology (Anubhav et al., 2025). The framework's emphasis on outside assistance as a facilitator of technology adoption is consistent with this (Venkatesh et al., 2003).

Technology Utilization in agriculture refers to both the intention to adopt and integrate innovative technologies into farming practices (Langer et al., 2024). This construct, rooted also in the UTAUT model ("Use Behavior" dependent variable), involves both external and psychological factors that influence a farmer's decision-making process. However, systemic and contextual factors, including financial limitations, regulatory support, technological infrastructure, and this desire, influence use behavior (Van Deursen et al., 2015; Mohr & Kühl, 2021). Based on this, the following hypothesis is examined:

> **H1: There is a positive relationship between Facilitating Conditions and Technology Utilization.**

Performance expectancy is "the degree to which using technologies improves individuals' performance" (Lee et al., 2024). Adoption rates are strongly influenced by how well AI solutions align with current farming methods and user expectations (Sood et al., 2023), as well as those that encourage AI-based sustainable agriculture solutions (Sood et al., 2024). According to these authors, fulfilling early expectations increases the likelihood of adopting and using technologies.

In considering this, the following hypothesis is tested:

H2: There is a positive relationship between Performance Expectancy and Technology Utilization.

Social influence: is the extent to which a person believes that significant others think they should utilize the new technology (Venkatesh et al., 2003) and it measures local community dynamics like agricultural cooperatives, social networks (Yadav et al., 2023), which facilitate the diffusion of innovations (Ronaghi & Forouharfar, 2020). In this context, we tested:

H3: There is a positive relationship between Social Influence and Technology utilization

Perceived Sustainability Advantages: measures how farmers think innovative agricultural technology supports sustainable development, including social justice, economic viability, and environmental preservation. Both personal values and the actual or predicted outcomes of implementing these technologies form the foundation of this perspective. Environmental sustainability is the reduction of adverse effects on the environment (e.g., protecting biodiversity, minimizing chemical input). Economic viability is the improvement of resource efficiency and profitability. Social equity is advancing higher living standards, food security, and ethical labor practices (Naspetti et al., 2017; Dash et al., 2024).

The inclusion of this additional variable is justified because existing adoption models, like UTAUT2, pay little attention to sustainability considerations, as they were initially adapted to other contexts. In the French context, where the Green Deal and the Common Agricultural Policy prioritize sustainability goals, farmers' perceptions of environmental, economic, and social outcomes greatly influence their willingness to adopt innovative technologies. Therefore, this framework fills a theoretical gap while highlighting an important contextual factor in technology adoption.

This dimension has been added to UTAUT to better understand the adoption of smart agriculture technologies. The advantages of sustainability are seen as demonstrating farmers' expertise in sustainable practices and their influence on technology utilization.

H4: There is a positive relationship between Perceived Sustainability Advantages and Technology Utilization.

Price Value (Perceived cost) is "the cost of acquiring and using a technology product compared to the benefit that comes from using the product" (Moya et al., 2018). Farmers consider the potential yield and resource management benefits of deploying AI against the associated expenses, which may significantly impact their decision (Sood et al., 2023). Farmers who believe technology is advantageous will likely adopt it (Pino et al., 2017). Based on this framework, we tested the indirect effects between these four hypotheses.

H5: There is a positive relationship between Facilitating conditions and Technology Utilization mediated by Price Value.

H6: There is a positive relationship between Performance Expectancy and Technology Utilization mediated by Price Value.

H7: There is a positive relationship between Social Influence and Perceived Sustainability Advantages mediated by Price Value.

H8: There is a positive relationship between Social Influence and Technology Utilization mediated by Price Value.

Those models complete each other by including many variables centered on technological acceptance. Every theory is distinct and describes various facets of the technology adoption process, as well as the variables influencing behavioral change. Our approach deliberately excludes Behavioral Intention, as the study focuses on actual technology use rather than intention to adopt.

The adoption of technology in agriculture differs significantly from its application in other fields. Most farmers are used to depending only on their intuition and expertise. New technology and solutions reduce time and funds without losing reliability and expectations. Our research aims to understand all the variables that influence farmers' decisions to implement innovative solutions, considering government subsidies and contributions, as well as recently enacted legislation supporting sustainability.

These frameworks cover several aspects of the technology adoption process. They have a comprehensive understanding of the psychological and behavioral factors that affect farmers' choices.

The theoretical model (Figure 1), which includes the previously mentioned variables and the hypotheses that link them, is presented below.

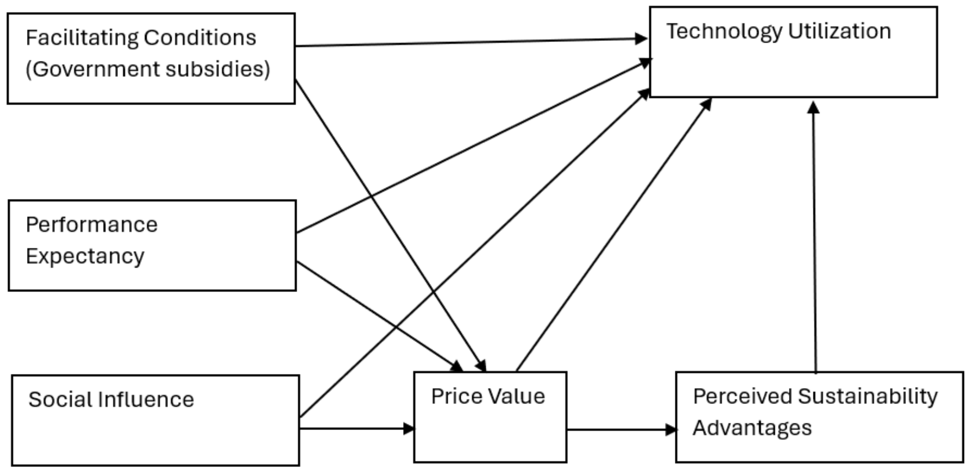

Figure 2. French Farming Innovation Adoption Model (FFIA Model)

The FFIA (French Farming Innovation Adoption) model above proposes an agricultural adaptation of the UTAUT2 framework. It provides a more nuanced understanding of how farmers evaluate and adopt innovative technologies in response to economic and environmental pressures. This nuanced understanding is crucial in the developing field of agricultural technology and innovation adoption. The theoretical model presented above aims to design and examine the primary factors influencing the adoption of technology in agriculture.

3 Methodology

This study examines the factors influencing Perceived Sustainability Advantages and technology adoption. Based on our literature review, we explore how technological, Price-Value, Performance Expectancy, and Facilitating Conditions (Including Government Subsidies) shape technology utilization with Perceived sustainability advantages.

To achieve a comprehensive understanding, we used a mixed-methods approach, combining qualitative and quantitative research through triangulation.

Initially, we planned to conduct 17 interviews, following guidance that suggests 12 to 18 interviews are Usually enough to achieve thematic saturation in qualitative research (Guest et al., 2006; Hennink et al., 2017; Creswell, 2013). However, five of the selected farmers were unavailable due to time constraints, so we conducted interviews with the remaining 12. Their responses allowed us to modify and improve the questionnaire administered to 189 French farmers who are effective in technology utilization, based on discussions and their critical opinions. questionnaires were distributed via the Chamber of Agriculture, farmers (students' parents or uncles), and an alumni network of agronomy engineers. After data cleaning, we retained 171 valid responses, removing outliers through Python coding to ensure the reliability of our findings.

Using Structural Equation Modeling (SEM) with SmartPLS, we test multiple hypotheses to assess the significance of these factors. Our analysis explores direct effects (e.g., the influence of cost efficiency on Performance Expectancy), moderating effects (e.g., the role of age in the relationship between Trust in technology and Adoption), and overall usage behaviors.

3.1 Research Method Design

Our study builds on the UTAUT theory, to which we have added the variable “Sustainability Advantages Perceived." This variable guided our selection of factors to analyze their impact and the relationships between them. The following table summarizes the variables, associated indicators, and the literature that supports our choices.

Table 2. Dimensions, Indicators, and Theories

Dimension/construct	Indicators	Literature / Source
Performance Expectancy	10- IS_expectations 8- Expect_imp	Venkatesh et al. (2003) Sood et al. (2023) Lee et al. (2024)
Social influence	23- soc_inf 23- soc_inf_colleagues- social med 23- soc_inf_fam_friends	Venkatesh et al. (2003) Ronaghi and Forouharfar, 2020
Facilitating Conditions	24- Subsidies Gov 25- Gov Politics subsidies	Anubhav et al. (2023) Wu et al. (2022)
Technology Utilization	15- Use intention 1- Use connected capt	Davis et al. (1989) Venkatesh et al. (2003) Van Deursen et al., (2015) Mohr and Kühl (2021) Taheri et al. (2022) Langer et al. (2024)
Sustainability Advantages Perceived	16- SI_agri_sustainability 17- Perc_integ_IS Sus	Naspetti et al. (2017) Otter et al. (2023) Thomas et al. (2023)
Price Value	13- Econ adv / cost imp 13 a- Use new tech	Venkatesh et al. (2003) Pino et al. (2017) Sood et al. (2023) Stevens and Stetson (2023)

3.2 Qualitative Study: Content Analysis

To systematically analyze the qualitative data gathered from our 12 interviews, we used content analysis, which is used "…for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use." Krippendorff (2019) examines communication content by identifying trends and implications in texts, images, or media. It is widely used in social sciences and communication research to analyze qualitative data methodically. This approach allowed us to go beyond simply describing individual interviews and identify shared motivations, barriers, and perspectives about technology adoption. The transcripts were structured into thematic categories based on both our theoretical framework and findings (Table 1, with primary interviews provided in Appendix A).

Table 1. Categorization

Theme	**Categories**
Barriers to the Adoption of Smart Solutions in Agriculture	Digital Anxiety Lack of Practical Replacement Time-Consuming Learning Lack of Interoperability Regulatory Limitations High Costs and Low Profitability
Impact of Policies and Subsidies on Adoption	Complex and Insufficient Funding Unintended Price Inflation Distortion of Agricultural Practices Negative Policy Consequences Lack of Government Support
Concerns About Agricultural Data Management	Data Exploitation Security Risks Lack of Data Utilization Tools Underutilization of Existing Data
Adaptation of Smart Solutions to Different Farm	Labor Shortages in Livestock Farming

Types	Lack of Consideration for Diverse Farming Models Mismatch with Polyculture Farming Lack of Specificity in Assessing Technologies
Personal Experiences with Smart Solutions in Agriculture	Failed Technological Investment Resistance from Service Providers Economic and Geopolitical Constraints Commitment to Sustainable Practices

The findings above (Table 1) show that Farmers face various psychological and technological challenges, particularly in developing countries (Ncube et al., 2023), when adopting new technologies. Digital anxiety can cause uncertainty about new technology, which in turn limits its adoption. Furthermore, the effort necessary to understand and integrate these technologies may be perceived as discouraging.

The functional limitations of innovative solutions also present challenges. Direct observation and hands-on experience are essential in farming, and technologies may not always provide a complete solution. Furthermore, fragmented systems make it challenging to integrate various technologies, thereby complicating their adoption.

Regulatory barriers further slow the progress of innovation, and outdated legislation frequently fails to keep pace with technological changes, resulting in implementation delays. Similarly, complex administrative procedures can discourage farmers from exploring new alternatives.

Another significant limitation concerns the technological and financial costs associated with this approach. Many farmers cannot afford innovative technologies due to their high costs. Furthermore, although subsidies are intended to help, they can occasionally lead to price inflation, thereby complicating access to these innovations.

Innovative solutions must align with agronomic principles to be effective. These technologies can cause practice distortions and reduce usefulness if they do not integrate with farming workflows. Moreover, before adopting these solutions, farmers must observe a significant increase in profitability.

Restrictive policies also constrain farmers. Banning certain agricultural practices without viable alternatives puts them in a difficult situation. Furthermore, many people believe innovative solutions are intended to benefit technology firms rather than farmers, making them hesitant to adopt new tools.

3.3 Linking Qualitative to Quantitative Design

Qualitative study, a crucial precursor to the survey, played a pivotal role in shaping the FFIA model and informing the design of the quantitative instrument. The interviews revealed repeating themes related to barriers in adoption, including digital anxiety, poor interoperability between systems, insufficient training, and frustration with the complexity of government subsidies. These findings revealed a resistance to technology use, which led us to modify our focus. Rather than continuing to explore reasons for non-adoption, we chose to investigate the opposite: what motivates farmers who do use smart technologies. This shift in perspective enabled us to better understand the key drivers of adoption behavior. The qualitative findings directly informed the inclusion of constructs such as Facilitating Conditions (Government Subsidies) and Price Value in the model. In addition, the perceived gap between innovative technologies and the realities of farm work (e.g., in livestock or polyculture systems) is paired with the logic behind constructs like Performance Expectancy and Perceived Sustainability Advantages. In this way, the qualitative phase not only contextualized the theoretical model but also ensured that the constructs reflected the actual concerns and experiences of French farmers, thereby reinforcing the model's empirical and practical relevance.

3.4 Quantitative study : Descriptive Statistics

Building on the qualitative findings, we conducted a quantitative survey to test the hypothesized relationships among adoption factors. Descriptive statistics were used to summarize the characteristics of the farmer respondents and provide context for the subsequent structural analysis. Specifically, measures like the mean, median, standard deviation, and frequency distributions were employed to analyze demographic variables (e.g., age, education, farm size, income), offering a wider picture of the sample and identifying potential patterns in technology adoption (Field, 2024; Pallant, 2020).

Table 3. Descriptive Statistics

Categories	Subcategories	Frequency (N)	Percent %
Size	Less than 20 ha	2	0.01
	From 20 < 50 ha	2	0.01
	From 50 < 100 ha	15	0.09
	From 100 < 200 ha	54	0.32
	200 ha +	98	0.57
Education	Brevet	2	0.01
	Bac	22	0.13
	Bac + 2	31	0.18
	License	3	0.02
	Master	107	0.63
	Master Doctorat	6	0.03
Age	<20	14	0.08
	20-29	12	0.07
	30-39	18	0.11
	40-49	45	0.27
	50-59	59	0.35
	>60	20	0.12
	Missing values	3	

The demographic variables include the size of farms, the respondent's education, and age. Results show that most respondents hold a higher education degree (86%) and are over 40 years old (74%). According to the table above, we also notice that most farms are 50 hectares or higher (89%).

3.5 PLS - SEM

To examine the complex relationships between adoption factors, perceived sustainability advantages, and technology utilization, we employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS, a widely used method for studying agricultural technology adoption, particularly in analyzing complex relationships between variables. Some studies employed SmartPLS to explore factors influencing farmers' intention to use autonomous field robots (Rübcke von Veltheim et al., 2022). Similarly, Zhang et al., (2024) used SmartPLS to examine the factors influencing small rural farmers' adoption of new agricultural technologies, emphasizing the importance of hedonic motivation and facilitating conditions. These studies demonstrate how SmartPLS provides recommendations for effectively utilizing innovative agricultural technologies. However, the application of PLS-SEM has been the topic of intense methodological controversy. Evermann and Rönkkö (2021) questioned its statistical rigor, arguing that its extensive application in information systems research may have led to incorrect theoretical findings. In response, Sharma et al. (forthcoming) supported PLS-SEM as a robust and evolving method, particularly suitable for predictive research. In contrast, Goodhue et al. (2023) debated the generalizability of Evermann and Rönkkö's simulations, while emphasizing the method's practicality. Russo and Stol (2022) advocated a more balanced approach, cautioning against dismissing PLS owing to its limits and highlighting the relevance of contextual and philosophical appropriateness. These exchanges reflect an active scholarly conversation that eventually promotes the responsible and context-aware application of SmartPLS in practical research, such as agricultural innovation.

4 Results

4.1 Measurement Model and Path Analysis

The measurement model assessment begins with evaluating the reliability of the indicators. Individual indicator reliability is considered acceptable when the outer loadings exceed or equal 0.70 (Hair et al., 2019). This indicates that the latent variable explains at least 50% of the variance in each of the indicators. Indicators showing outer loadings between 0.40 and 0.70 should be eliminated only if their deletion increases composite reliability or Average Variance Extracted (AVE) above the suggested threshold (Hair et al., 2021).

Internal consistency reliability is traditionally assessed using Cronbach’s alpha, which should exceed 0.70.

However, researchers should also consider composite reliability (CR), which should be between 0.70 and 0.95, due to the limitations of Cronbach's alpha (Hair et al., 2019). Potential redundancy among indicators is indicated by values greater than 0.95 (Diamantopoulos et al., 2012).

AVE is used to evaluate convergent validity, and it should be higher than 0.50 (Fornell & Larcker, 1981). This threshold ensures that the latent variable explains more than 50% of the variance in its indicators.

Path coefficients represent standardized beta coefficients from ordinary least squares regressions. The significance of path coefficients should be assessed through bootstrapping procedures to obtain t-values and confidence intervals (Hair et al., 2021).

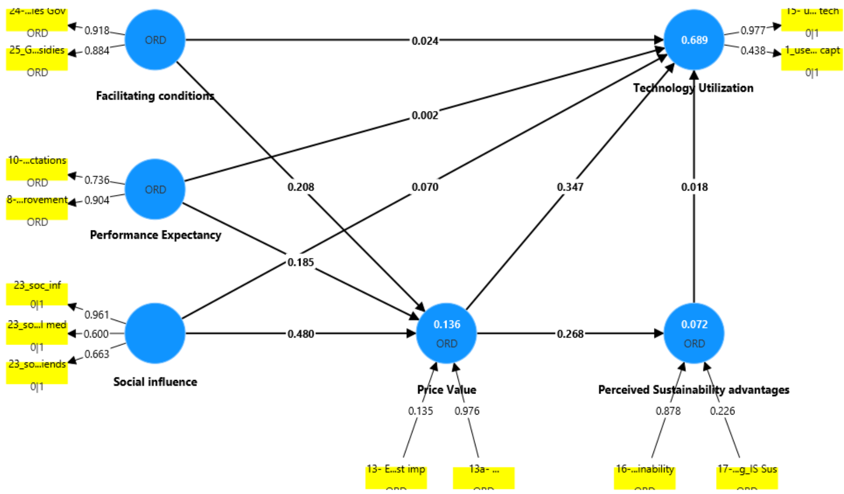

Figure 4. PLS-SEM Model

The structural model's findings, which illustrate the relationships between the study's key variables, are presented in Table 4. All the model's direct effects are presented in this table. Since they offer an expanded view of the mediated relationships between variables, only the significant indirect effects have been kept for additional analysis.

Table 4. Direct and Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDV|	P values	Strength Classification
Direct Effects :						
Facilitating conditions -> Price Value	0,208	0,211	0,078	2,686	0,007	Moderate
Facilitating conditions -> Technology Utilization	0,024	0,024	0,022	1,102	0,270	Not significant
Performance Expectancy -> Price Value	0,185	0,190	0,081	2,273	0,023	Moderate
Performance Expectancy -> Technology Utilization	0,002	0,003	0,020	0,084	0,933	Not significant
Price Value -> Sustainability advantages Perceived	0,268	0,280	0,071	3,771	0,000	Moderate
Price Value -> Technology Utilization	0,347	0,345	0,019	18,575	0,000	Strong
Social influence -> Price Value	0,480	0,528	0,192	2,501	0,012	Strong
Social influence -> Technology Utilization	0,070	0,074	0,060	1,171	0,242	Not significant
Perceived Sustainability Advantages-> Technology	0,018	0,017	0,020	0,889	0,374	Not significant

Utilization						
Indirect Effects						
Facilitating conditions -> Sustainability advantages Perceived	0,056	0,060	0,029	1,929	0,054	Not Significant (marginal)
Facilitating conditions -> Technology Utilization	0,073	0,074	0,027	2,701	0,007	Weak
Performance Expectancy -> Sustainability advantages Perceived	0,049	0,054	0,029	1,714	0,087	Not significant
Performance Expectancy -> Technology Utilization	0,065	0,067	0,029	2,243	0,025	Weak
Price Value -> Technology Utilization	0,005	0,005	0,006	0,839	0,401	Not significant
Social influence -> Sustainability advantages Perceived	0,129	0,148	0,067	1,917	0,055	Marginal
Social influence -> Technology Utilization	0,169	0,184	0,067	2,531	0,011	Moderate

4.2 Quality Criteria and Bootstrapping

To validate the structural model, bootstrapping was conducted along with evaluations of R2, AVE, Composite Reliability (ρC), and Discriminant Validity (HTMT). While AVE measures convergent validity with a limit of 0.50, R2 measures the model's explanatory power (Fornell & Larcker, 1981). To ensure reliability, Composite Reliability (ρC) is used to measure internal consistency. The Heterotrait-Monotrait Ratio (HTMT), which is used to confirm discriminant validity, verifies that constructs are distinct (Henseler et al., 2015).

Table 5. Collinearity Statistics

	VIF		VIF
10- IS_expectations	1,165	1_use connected capt	1,058
13- Econ adv / cost imp	1,013	23_soc_inf_colleagues_social_m	1,013
13a- Use intention/cost	1,013	23_soc_inf_fam_friends	1,013
15- use new tech	1,058	24- Subsidies Gov	1,645
16- SI_agri_sustainability	1,252	25_Gov Politics subsidies	1,645
17- Perc_integ_IS Sus	1,252	8- Expect_improvement	1,165
23- Social Influence			

The collinearity statistics, specifically the Variance Inflation Factor (VIF), indicate that all variables have values close to one, suggesting no significant multicollinearity among the independent variables and confirming the model's validity.

Table 6. R-Square

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Price Value	0,136	0,162	0,050	2,737	0,006
Perceived Sustainability Advantages	0,072	0,083	0,040	1,806	0,071
Technology Utilization	0,689	0,697	0,031	22,163	0,000

The R^2 results show that the model explains 68.9% of the variance in Technology Utilization, indicating strong explanatory power. Price Value has an R^2 of 13.6%, suggesting a modest but acceptable level of explanation for exploratory research. Perceived Sustainability Advantages have a lower R^2 of 7.2%, with a marginal p-value (0.071), indicating weak but potentially meaningful insight for future studies. Overall, the model demonstrates strong predictive relevance for technology adoption behavior, with room for improvement in explaining intermediate variables.

Table 7. AVE, Rho C and Cronbach's Alpha

	AVE	Rho C
Facilitating conditions	0,812	0,896
Performance Expectancy	0,680	0,808
Social influence	0,574	0,795
Technology Utilization	0,573	0,701

The results indicate that all constructs meet the recommended thresholds for both convergent validity and composite reliability. Each construct has an Average Variance Extracted (AVE) above 0.50, confirming that the items adequately capture the variance of their underlying latent constructs. Facilitating Conditions demonstrates powerful performance, with an AVE of 0.812 and a Rho C of 0.896, reflecting excellent construct reliability and internal consistency.

Performance Expectancy, Social Influence, and Technology Utilization also demonstrate acceptable levels of convergent validity (AVE = 0.680, 0.574, and 0.573, respectively) and reliability (Rho C = 0.808, 0.795, and 0.701). While these values are somewhat lower than those for Facilitating Conditions, they still exceed the minimum recommended threshold of 0.70 for Rho C, confirming acceptable reliability.

Table 8. Discriminant Validity Heterotrait-monotrait ratio (HTMT) - Matrix

	Original sample (O)	Sample mean (M)	2.5%	97.5%
Performance Expectancy <-> Facilitating conditions	0,437	0,445	0,249	0,658
Social influence <-> Facilitating conditions	0,213	0,237	0,124	0,364
Social influence <-> Performance Expectancy	0,154	0,232	0,108	0,390
Technology Utilization <-> Facilitating conditions	0,507	0,536	0,245	0,918
Technology Utilization <-> Performance Expectancy	0,432	0,505	0,243	0,930
Technology Utilization <-> Social influence	0,386	0,459	0,191	0,891

Table 8 presents the Heterotrait-Monotrait Ratio (HTMT) values, which assesses discriminant validity between constructs. The highest HTMT value is between Technology Utilization and Facilitating Conditions (HTMT = 0.507), which remains within acceptable limits. The weakest relationship is between Social Influence and Performance Expectancy (r = 0.154), confirming a good separation between these latent variables. Most values are below the 0.85 limit (Henseler et al., 2015), indicating that the constructs are distinct.

Below is a table displaying the Q^2predict values:

Table 9. Q2 Predict

	Q^2predict
Price Value	0,077
Perceived Sustainability Advantages	0,064
Technology Utilization	0,165

Table 9 presents the Q^2 Predict values for the model's endogenous constructs. All constructs demonstrate positive Q^2 values, indicating that the model has predictive relevance. Specifically, Technology Utilization shows moderate predictive power ($Q^2 = 0.165$), while Price Value ($Q^2 = 0.077$) and Perceived Sustainability Advantages ($Q^2 = 0.064$) demonstrate weak but acceptable predictive relevance.

The results of the hypotheses are presented in the table below:

Table 10. Hypotheses Results

	Validated or refuted
H1: There is a positive relationship between Facilitating Conditions and Technology Utilization.	Refuted
H2: There is a positive relationship between Performance Expectancy and Technology Utilization.	Refuted
H3: There is a positive relationship between Social Influence and Technology Utilization.	Refuted
H4: There is a positive relationship between Perceived Sustainability Advantages and Technology Utilization.	Refuted
H5: Facilitating Conditions positively influence Technology Utilization indirectly.	Validated
H6: Performance Expectancy has a positive indirect influence on Technology Utilization.	Validated
H7: Social Influence positively influences Perceived sustainability advantages indirectly.	Partially Validated
H8: Social Influence positively influences Technology Utilization indirectly.	Validated

5 Discussion

Regarding our first research question, **RQ1:** What factors influence French farmers' adoption of innovative Technologies, the results indicate that Facilitating Conditions—including government subsidies, social influence, and performance expectancy (H5, H6 and H8)—affect technology adoption, with Price value as a mediator. Results show that farmers prioritize price value in the short term to maintain a safety margin for future investments.

Regarding our second research question, **RQ2:** Does the perception of sustainability affect French farmers' adoption of innovative technologies?

Our analysis shows that perceived sustainability benefits do not significantly drive the actual use of agricultural technologies (H4). In other words, even when farmers recognize potential environmental or sustainability improvements, this perception alone does not encourage them to adopt or implement new technologies.

Let's explore our results further: The analysis of the hypotheses provides insight into how various factors, such as Price Value, Technology Advantages, and Facilitating Conditions, influence Perceived Sustainability Advantages and Technology Utilization within the French agricultural context.

First, Price Value is frequently identified as an essential driver in relationships with other variables (Moya et al., 2018). The current results confirm this, showing a strong and significant positive relationship between Price Value and Technology Utilization ($\beta = 0.347$, $p < 0.001$). However, Technology Utilization is not directly influenced by its classic immediate predictors. Specifically, H1, H2, H3, and H4 were all refuted, meaning that Facilitating Conditions, Performance Expectancy, Social Influence, and Perceived Sustainability Advantages do not have direct effects on Technology Utilization.

The hypothesis (previously H4) suggesting that farmers' perceptions of sustainability advantages would directly affect Technology Utilization is also refuted, due to the weak and non-significant relationship. This suggests that while farmers may recognize and appreciate the sustainability benefits of new technology, this appreciation does not significantly influence their decision to invest in or utilize it (Gemtou et al., 2024). It implies that technologies may achieve broader adoption if they are not only sustainable but also perceived as cost-effective, user-friendly, and aligned with immediate agricultural goals.

These findings highlight how economic and strategic considerations, rather than purely technical or social ones, drive technology usage. The assumption that perceived benefits influence farmers' financial concerns and openness to innovation is supported by the finding that Social Influence has a significant impact on Price Value ($\beta = 0.480$, $p = 0.012$). This indicates that farmers who feel socially supported or influenced may translate that influence into economic perceptions, reinforcing the role of value in adoption decisions (Anastasiou, 2023; Moya et al., 2018).

The results also show that Facilitating Conditions ($\beta = 0.208$, $p = 0.007$) and Performance Expectancy ($\beta = 0.185$, $p = 0.023$) both have significant moderate effects on Price Value, confirming that government support and perceived usefulness influence adoption indirectly via cost-benefit considerations. These relationships highlight the significance of economic mediation, where institutional or technical support becomes meaningful only when it influences how farmers evaluate financial value.

Interestingly, the model does not include government subsidies directly. However, the significant paths from Facilitating Conditions and Performance Expectancy to Price Value support the idea that subsidies or external support mechanisms may still play a role, although indirectly. These findings refine previous assumptions that government support has a direct impact, suggesting instead that its influence is conditional on how it affects perceived financial return. This partially contradicts studies like Anubhav et al. (2025), which found direct effects of government support on adoption. As noted by Wu et al. (2022), variability in policy implementation and sector-specific conditions may explain these differences.

Moreover, Technology Advantages (reflected in Performance Expectancy and Social Influence) show moderate to strong indirect effects on Technology Utilization through Price Value. That is, the more farmers perceive technologies as advantageous, the more likely they are to use them, if they believe they are worth the cost. This confirms the mediating role of Price Value and reinforces the argument that financial logic shapes behavioral intention in farming.

In addition, Technology Advantages positively influence Perceived Sustainability Advantages, as shown by the significant path from Price Value to Perceived Sustainability Advantages ($\beta = 0.268$, $p < 0.001$). This supports the view that farmers who see economic value in innovation are also more likely to perceive environmental benefits. Naspetti et al. (2017) similarly found that farmer decision-making around sustainability is shaped by peer influence and network-based interaction, especially when such innovations are framed in terms of practical benefits.

In summary, the analysis of the hypotheses reveals that Facilitating Conditions, Performance Expectancy, and Social Influence are not directly linked to Technology Utilization (H1–H4 are refuted). However, they do have indirect effects via Price Value (H5–H8 supported). These findings highlight the central mediating role of economic perception, offering a deeper understanding of how farmers evaluate technology—through both strategic and financial lenses—when making decisions about adoption and sustainability investments.

5.1 Theoretical Implications

This study contributes to the Information Systems (IS) literature by offering an agricultural adaptation of UTAUT2 that integrates cost–benefit evaluation through Price Value and domain-specific constructs, such as Sustainability Advantages Perceived. While UTAUT2 posits that constructs like Performance Expectancy, Facilitating Conditions, and Social Influence directly affect behavioral intention, our results demonstrate that in agricultural contexts, these effects are primarily indirect, occurring through economic appraisal.

This does not contradict UTAUT2 but instead refines its application by showing that Price Value acts as a cognitive filter, consistent with the Value-based Adoption Model (VAM) (Kim et al., 2007). Farmers are more likely to adopt technologies when benefits such as ease of use or environmental impact are translated into perceived economic gains.

Furthermore, the non-significant direct effect of government-related factors (e.g., subsidies) challenges past research (David et al., 2000; Anubhav et al., 2025), which often highlighted their direct role in adoption. Our results suggest that government support may indirectly shape adoption through its impact on perceived value. This suggests a shift from policy-driven adoption to value-driven adoption, where incentives must be perceived as beneficial to influence behavior.

Another important theoretical contribution is the inclusion of perceived Sustainability Advantages as a measured construct. While many agronomic studies assess sustainability through its outcomes (e.g., emissions reduction, soil quality), few have investigated how farmers perceive the benefits of sustainability and how these perceptions influence their adoption. For example, Liu & Liu (2024) found a link between technology and sustainability, though their study differs from ours in its approach. This adds a new dimension to IS adoption models by linking perceived Sustainability with Technology Utilization.

5.2 Practical Implications

The findings have important implications for practitioners, especially policymakers and Agri-tech developers. Given that Price Value is the strongest direct predictor of technology utilization, efforts should focus on making technologies more cost-effective and communicating their economic benefits. Farmers are more likely to adopt tools they perceive as financially worthwhile, rather than simply sustainable or socially recognized.

Subsidies, while important, do not directly drive adoption. Their impact can be enhanced if paired with complementary measures, such as technical assistance, cost calculators, or clear cost-benefit returns. Providing farmers with clear, accessible information on the economic impact will likely increase their willingness to invest in new technologies. Therefore, policy initiatives should not only lower the risks associated with initial investments but also show how innovations support labor rationalization and productivity gains. This would match financial incentives with farmers' operational realities, facilitating the efficient transfer of innovation.

Furthermore, the results show that perceived sustainability alone does not lead to adoption. Therefore, communication strategies should avoid relying solely on environmental messaging. Instead, messaging should link sustainability to profitability, highlighting how environmental practices can also reduce long-term input costs or improve yields. Enhancing farmer-to-farmer demonstration projects, cooperative-led programs, and community involvement may reduce resistance to innovation and promote common goals for sustainability.

Finally, technology developers should prioritize features that farmers associate with practical advantages and enhance trust through peer testimonials or cooperatives. Instead of focusing only on sustainability stories, technology providers could highlight the cost-benefit advantages (such as a decrease in input waste, labor optimization) and productivity gains (such as yield increases, optimized resource utilization). Additionally, certification, transparency in data usage, and intuitive user interfaces will strengthen confidence and promote long-term use. Since social influence has only an indirect effect, farmer-to-farmer communication, especially when framed in terms of economic value, may be one of the most effective levers for adoption and should be used as a strategic driver.

5.3 Limitations

The first limitation is that access to resources varies across farming communities. This limitation acknowledges that farmers' ability to adopt new technology is significantly impacted by their access to financial resources, education, infrastructure, and support services.

The second limitation is the total number of respondents. Farmers receive numerous questionnaires throughout the year, particularly those related to food quality and harvesting procedures. Over time, this has reduced receptivity, making it challenging to gather responses to our questionnaire.

Another limitation concerns the scope of our mixed-methods approach. While the qualitative interviews provided deeper insights into the motivations of resistant farmers and their adoption decisions, the small number of interviews limits the broad applicability of the qualitative findings.

A final limitation concerns the geographic scope and respondent profiles, as the sample mainly consisted of alumni, regional farmers, and members of the agricultural chamber of northern France.

6 Conclusion

Finally, the objective of our study was to investigate farmers' acceptance and adoption of technology, as well as their perception of the need to implement sustainable practices. We received two different types of responses. For the resistant farmers, we conducted open-ended interviews to gain a deeper understanding of their resistance to adopting new technologies. We administered a questionnaire for our quantitative study to the farmers who had already adopted the technology. The results showed that the main pivotal factor for technology acceptance is Price Value, the primary variable affecting technology use, rather than Government Subsidies. On the contrary, the farmers we interviewed who showed reluctance to adopt technology mainly cited digital anxiety and the time required to train on new technologies. They also mentioned outdated legislation and costs, which align with the findings of the quantitative study, indicating that these factors can complicate the adoption process. They are also reluctant because limited technical skills in new technology can hinder its adoption. For this reason, the involvement of Advisory Organizations, Chambers of Agriculture, and Technical Institutes is also crucial in informing and motivating farmers to adopt sustainable methods and to be less resistant. They should focus on demonstrating the advantages of technology to encourage its adoption and drive sustainability (Gemtou et al., 2024; Mizik, 2021).

The recommendations remain to focus on sustainability, design, and the responsible use of digital technologies (Corbett et al. 2023), particularly in agriculture, which constitutes one of the key levers for achieving the Sustainable Development Goals. In this context, it would be ideal to align government subsidies and support programs with the actual costs of adopting new technologies—by offering targeted training sessions and regular meetings with farmers. These initiatives could help them gradually integrate digital tools without feeling overwhelmed or left behind, especially in comparison to large-scale operations.

In the future, it would be interesting to conduct a study targeting small farms to better understand which technology they are willing to adopt.

Declaration of AI

The AI tools (Copilot, Scispace, Perplexity and Grammarly pro edition) were used to reformulate small paragraphs and search for authors and papers. It also helped verify the analysis results.

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Appendix A: Detailed Content Analysis

Themes	Main Findings
Barriers to the Adoption of Smart Solutions in Agriculture	Farmers feel stress and have difficulty navigating applications and screens.
	Smart solutions do not eliminate the need for direct observation of crops and livestock.
	Managing multiple tools requires significant time for learning, data tracking, and analysis.
	Many solutions lack compatibility between brands and systems, reducing efficiency.
	Drone regulations are outdated and do not accommodate agricultural use
	Smart technologies have high costs, limited ROI, and face regulatory challenges.
Impact of Policies and Subsidies on Adoption	Subsidies (PCAE) are depleted too quickly, making application preparation difficult.
	Subsidies contribute to rising prices of smart technologies.
	The new CAP's eco-scheme prioritizes economic over agronomic crop rotation.
	Subsidies reduce farm profitability instead of supporting investment.
	Farmers feel policies impose restrictions without providing viable alternatives.
Concerns About Agricultural Data Management	Farmers worry that their data may be used by third-party companies without financial compensation. The geopolitical situation raises concerns about data security.
	There is a shortage of software to compile and analyze agricultural data for decision-making.
	Valuable data, like soil maps, are not integrated into available agricultural software.
Adaptation of Smart Solutions to Different Farm Types	Automation is difficult in livestock farming, where labor shortages are more pressing.
	The survey focuses on large-scale and intensive dairy farming, neglecting resilient and intelligent farming models.
	Farmers in regions like Eure-et-Loir find the survey out of touch with their realities.
	The survey generalizes too many technologies (GPS, sensors, weather tools, etc.), making evaluation difficult.
Personal Experiences with Smart Solutions in Agriculture	A farmer invested €6M in a farm management software project but couldn't complete it due to financial constraints.
	Tech providers resist collaboration, hindering digital transformation.
	In the current unstable climate, investing in new technologies is not a priority.
	Some farmers engage in agro-environmental measures (e.g., MAEC with adapted crop rotation).

About the Authors

First Name Last Name. After the references and the appendices, if there are any, come short biographical sketches of each author. The bios should be in normal text format, with a separate bio for each author. Put the author's name in bold at the start of the bio. Do not include titles such as "Dr." or "Professor". Italicize all journal titles in the biography. If referencing the *Communications of the Association for Information Systems,* spell out the entire name of the journal, just as in this sentence, rather than using the acronym for AIS. The maximum length of each biography should be approximately 150 words. Do not include email addresses.

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