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Smart agriculture as source of sustainability in intensive greenhouse production

RESEARCH ARTICLE

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Abstract

The article addresses the interaction between smart agriculture and sustainability within the specific context of intensive greenhouse agriculture in southeast Spain. Combining a literature review and expert interviews, the methodology is based on a qualitative data analysis, whose main goal is to gain a comprehensive understanding of the phenomenon under study. The results identify three key areas of technology that strongly influence this type of agriculture. The first relates to soil, water savings, sensor utilization, and environmental improvement, while the second encompasses robot use, labor reduction, resulting cost improvement, and economic sustainability. Finally, the third group, albeit of lesser importance, links artificial intelligence with ethical issues such as data control, usage, and technological dependence. In summary, the application of smart agriculture is projected to have positive impacts on economic and environmental sustainability, relegating the social dimension to a more distant level. This imbalance suggests that social and ethical aspects could be subordinated to more immediate benefits. The results also suggest that the need for future investments could create polarization in the sector. Not all farmers and businesses can afford these investments, leading to progressive deterioration and even abandonment of agricultural activities in some cases.

Keywords: smart agriculture, sustainability, value chain
JEL code: Q15 Q16

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1. Introduction

The agricultural sector currently faces significant challenges, including climate change, global population growth, loss of biodiversity, and a scarcity of productive inputs. Approximately 25% of cultivable land is estimated to be degraded (FAO, 2011). By 2030, it is projected that the supply of water will be 40% insufficient to meet global water needs (United Nations, 2016). Estimates indicate that by 2050, there will be a need to produce 60 to 70% more food; however, no significant changes in available land are expected (Odegard and van der Voet, 2014). This requires a different model that must be more efficient and environmentally friendly (Food and Agriculture Organization of the United Nations, 2011). Furthermore, agriculture and food production are significant consumers of water and energy (Roidt and Avellán, 2019). The factors of water, energy, and food (WEF) are considered strategic resources for any economy (Purwanto *et al*., 2019), as reflected in the Sustainable Development Goals (Babatunde *et al*., 2019). The main challenge is to ensure a sufficient supply of water, energy, and food under extremely uncertain conditions, as seen at present (Zhang *et al*., 2018).

In recent years, digitalization of agriculture has been proposed as one of the most relevant drivers to overcome these challenges (Klerkx *et al*., 2019). Although the application of new technologies in agricultural activities is currently in its early stages and is gradually being implemented, with significant variations between agricultural sectors, intensive greenhouse agriculture is emerging as a pilot implementation system, owing, in part, to its innovative predisposition (García-Granero *et al*., 2020). This article specifically addresses the case of intensive greenhouse agriculture in southern Spain, a region which is a major supplier of horticultural products in Europe, contributing to more than 40% of the vegetables imported in autumn and winter on the continent (Andalusian Ministry of Agriculture, 2024). Despite possessing a lower technological level compared to greenhouses in northern Europe (such as the Netherlands or Belgium), those in southern Spain (36 372 ha) are more energy efficient. Nevertheless, there is a strong interest in implementing new technologies in this region due to their potential for resource optimization and improved management. Such technologies include soil sensors, pest remote sensing, robotics, and intelligent climate control.

In this context, the main objective of the article is to analyse the role of specific smart and precision agricultural technologies in intensive greenhouse production and how they can influence its economic, social, and environmental sustainability. Additionally, the study examines the ethical implications of these technologies, such as data management and ownership, as well as power distribution, aspects often overlooked in this type of research.

To achieve these objectives, the article begins with a description of smart and precision agriculture, including goals, uses, and constituent technologies. With reference to the specific sector analysed, a previous survey of the current degree of incorporation of this type of technology is carried out. While this information serves as a basis for conducting semi-structured interviews with key professionals in the production sector, aiming to identify the most significant, current technologies and their positive or negative impacts on intensive greenhouse horticulture production, ethical implications will be explored as well. The choice was made to speak to experts as they not only possess in-depth knowledge in their fields, but also offer critical perspectives, identify emerging trends, and propose innovative approaches that may not have been formally documented (Busse *et al*., 2014; Kutter *et al*., 2011). Furthermore, information was also collected from innovative farmers (Knierim *et al*., 2019). Data obtained from interviews is reviewed using qualitative data analysis techniques. Simultaneously, through a structured questionnaire based on weighting matrices (Saaty), the article analyses how these technologies impact sustainability by weighing their effects.

2. Conceptualization of smart agriculture

Smart Agriculture, or Smart Farming (SF), is the integration of modern Information and Communication Technologies (ICT) with a data-driven approach to address challenges and opportunities in agriculture

(Hoste *et al*., 2017). As explained by Wolfert *et al*. (2017), SF is a development that emphasizes the use of information and communication technology in the cyber-physical farm management cycle, which means that smart devices - connected to the Internet - are controlling the farm system. On the other hand, according to the International Society for Precision Agriculture (2021), Precision Agriculture (PA) is a management strategy that collects, processes, and analyses individual, spatial, and temporal data. Said data is combined with other information to support management decisions based on estimated variability, with the aim of improving efficiency in resource use, productivity, quality, profitability, and sustainability in agricultural production. It is a technology-driven revolution focused on maximizing production while minimizing or optimizing inputs and resources (Bakhtiari and Hematian, 2013). It is important to note that while PA only considers in-field variability, SF expands the concept by basing management tasks not only on location but also on data, enhanced by context and situation awareness, triggered by real-time events (Wolfert *et al*., 2017).

Smart Agriculture focuses on three fundamental aspects or steps: (1) capturing variability, (2) analysing said variability, and finally (3) supporting decision-making. Variability refers to the set of spatial and temporal factors associated with input management that will affect final yield (Kitchen and Clay, 2018). In this initial data collection phase, various technologies, mainly sensors, are typically used (Shibusawa and Haché, 2009). Once the data are generated in the initial stage, the second phase involves evaluating them to obtain meaningful interpretations and decisions. Statistical tools, software, and mathematical algorithms are used to draw significant conclusions based on captured data (Oliver, 2013; Panayi *et al*., 2017).

In summary, Smart Agriculture involves making informed decisions based on the analysis of analysed variables, determining when to act at the right moment (Ahmad and Dar, 2020). The ultimate goal of smart agriculture is to ensure a more sustainable agricultural activity (FAO, 2024), as its objectives include preventing soil degradation, trying to avoid resource depletion, reducing negative environmental impact and improving people's livelihoods (Ahmad and Dar, 2020). These four factors underpin the need to implement precision agriculture (Figure 1), which addresses the gap between potential and actual yield, known as the yield gap (Mayberry *et al*., 2017).

There are many different factors that contribute to soil degradation (Gupta and Kumar, 2018): excessive exploitation, deforestation, increased use of chemicals, erosion, as well as climate change and industrialization

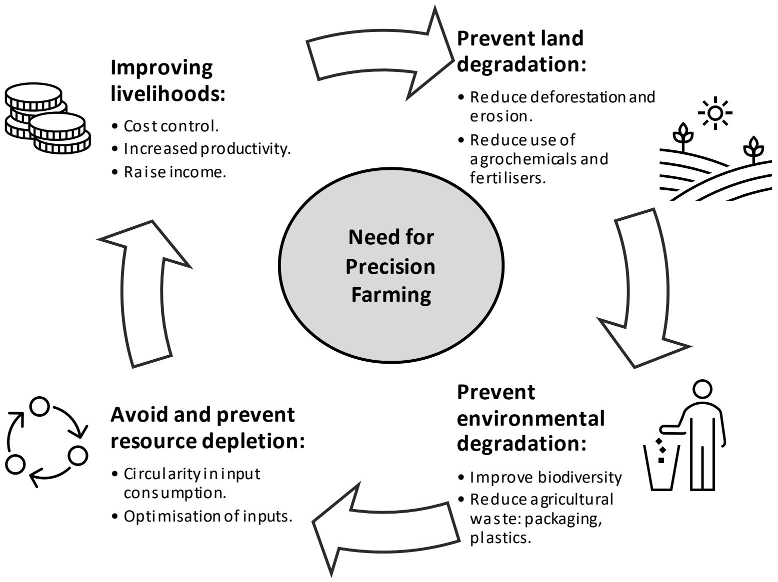

Figure 1. Standard reasons justifying the need for the adoption of precision agriculture. Source: Own elaboration based on Ahmad and Dar (2020).

(Bhattacharyya *et al*., 2015). Precision agriculture facilitates the implementation of holistic measures that combine soil resources with appropriate inputs, thus avoiding overexploitation (Gomiero, 2016). Concerning resource depletion, precision agriculture has the potential to improve the circularity and optimization of productive inputs (Bongiovanni and Lowenberg-DeBoer, 2004; Struik and Kuyper, 2017). Regarding environmental degradation, precision agriculture aids in waste management, reducing pollution while promoting biodiversity (Lindblom *et al*., 2017). Ultimately, precision agriculture contributes to improving livelihoods, improving skills and competitiveness in the areas where it is implemented (Jenrich, 2011). On the other hand, it helps control costs through increased productivity (Bach and Mauser, 2018; Bongiovanni and Lowenberg-DeBoer, 2004). Despite the aforementioned information, the adoption of PA faces challenges due to potential drawbacks, such as (Klerkx *et al*., 2019): (1) high investment, which is often overlooked when assuming universal adoption; (2) the current effectiveness of these technologies and their cost; (3) farmers' adaptation problems; and (4) or even aspects related to data control and privacy.

3. Smart agriculture in greenhouses

Greenhouse cultivation is one of the most dynamic activities in agriculture, representing an ideal cultivation system to implement most of the technologies that make up smart agriculture (Kavga *et al*., 2021; Vásquez *et al*., 2015). The greenhouse is poised to be a key element in future agriculture (Zhou *et al*., 2016), as it allows controlling plant growth variables, maximizing yields, and increasing efficiency (Reddy, 2016) by optimizing space, achieving efficient water and fertilizer consumption, and exerting better control over pests and diseases, among other benefits (Jha *et al*., 2019). Currently, traditional technology used in greenhouses for sustainable production goals is related to irrigation and climate control systems. Incorporation of more innovative technologies is still limited, especially in less technologically advanced greenhouses in southern Europe. Farmer distrust in expected results (Skaalsveen *et al*., 2020) along with insufficient technical training are the main reasons for farmers' reluctance to implement smart agriculture. The existence of small farms also poses challenges (Kavga *et al*., 2021).

Noteworthy technologies in the greenhouse sector that generate the most interest among technical experts, include: (1) remote sensing; (2) robotics; (3) connectivity, device mobility and artificial intelligence (AI); and (4) simulation and modelling. These technologies, each designed for specific functions, exhibit interaction within a constant feedback process (Figure 2).

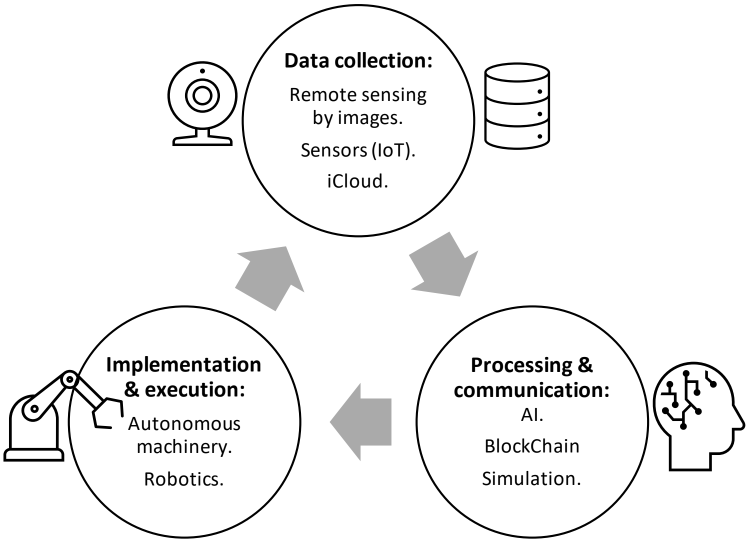

Figure 2. Main function and interaction among SFT. Source: Own elaboration.

Remote sensing is the technology that allows capturing information through noninvasive techniques, meaning there is no actual handling and manipulation of the object (Mountrakis *et al*., 2011). Its application in greenhouses involves the use of both optical and reflective soil sensors, as well as chlorophyll sensors or soil scanners (Aggarwal, 2004). Numerous variables in agriculture can be captured by remote sensing, including plant biomass, nutrient composition and deficiency, moisture levels, water stress, diseases, pest occurrence or degree of ripeness. Subsequently, all this information, which is stored and analysed with simulation or modelling techniques where AI plays a significant emerging role, will serve as a basis for decision making, including the optimization of fertilizers, irrigation, phytosanitary treatments, climate control, etc. (Ahmad and Dar, 2020). In the specific case of pest and disease detection and early warning, image processing and pattern recognition through the application of AI have obtained notable results (Mahlein, 2016; Vukadinovic *et al*., 2016), for example, disease detection at a much earlier stage (Hoste *et al*., 2017). Drones, adapted for greenhouse work (e.g., cablebot, using rails), despite their complexity of use in enclosed spaces, are also being tested as information gathering mechanisms (Kooistra, 2017; Thomopoulos *et al*., 2021).

With respect to robotics and other smart machinery, these technologies range from small robots to other types of autonomous agricultural machinery. Such machines or robots incorporate their own sensors and detectors to use information to improve existing models (Bechar and Vigneault, 2017; García Martnez, 2021). Thanks to this autonomous and intelligent machinery, farmers can save time and other resources, as it allows them to work faster and more precisely than a human (Mckinsey, 2020). The incorporation of AI, Big Data, low-cost sensors, as well as Graphics Processing Units (new processors for computationally intensive, AI-enabled modelling and simulation), will help replace tasks previously performed by humans (Hoste *et al*., 2017).

Connection and interconnectivity between devices, as well as computational development such as Artificial Intelligence (AI), play a predominant role in smart agriculture and, from a theoretical standpoint, there is no doubt that AI will increase efficiency in agriculture (Montes, 2021). The use of next-generation networks, Internet of Things or IoT, and shared information using iCloud technology allow the creation of collaborative solutions for sustainable crops, quick decision-making responses, and input optimization. AI and machine learning algorithms will enable agriculture to adapt to increasingly complex, extreme and changing external conditions (García Martínez, 2021). Integration of data from various sources (weather, irrigation and nutrients) improves and maximizes returns (McKinsey, 2020). On the other hand, increased connectivity will not only change the way a greenhouse is managed and monitored but can also contribute to the generation of much more innovative business models, highlighting its spillover effects (Ruan *et al*., 2020; KPMG, 2019).

Another specific example of the progress being made is the use of digital twins, which are defined as the digital equivalent of a real-world object that reflects its behavior and state throughout its life in a virtual space, making it a virtual model or replica of the real thing based on simulation (Boschert and Rosen, 2016; Grieves and Vickers, 2016). Digital twins, despite being a relatively recent technology, are also being applied in greenhouses. Their use can involve significant cost reductions, for example, through the prior simulation of technologies before their final implementation.

3.1 Extension of smart farming technologies (SFT) to the rest of the value chain

Smart farming technologies (SFT) are not only applicable in the production phase. They constitute an approach that will also serve to optimize each stage of the agricultural value chain, with the aim of maximizing efficiency, sustainability, and profitability in food production, from seed creation to when the product is acquired by the end consumer. This vision involves the convergence of smart farming with eco-innovative horticultural supply chains (García-Granero *et al*., 2020), or even with biotechnology (upstream), seeking the development of fully adapted crops based on data collection and interpretation (Agrimonti *et al*., 2021).

For example, technologies such as blockchain (Caro *et al*., 2018; Zhao *et al*., 2019) enable the creation of transparent and secure supply chains by tracking each stage of the process. This not only ensures the quality and safety of food, but also opens new opportunities for product differentiation and certification of sustainable practices. On the other hand, the introduction of robots into the vegetable production chain not only increases productivity but also addresses challenges related to labor, product quality, and operational efficiency (Duong *et al*., 2020). Furthermore, the implementation of IoT sensors (Verdouw *et al*., 2016) in the transport and storage of agricultural products allows real-time control of variables such as temperature, humidity, and storage conditions. This helps to maintain the quality of the product and prevent losses. Artificial intelligence (AI) and machine learning (Wolfert *et al*., 2017; Ahearn *et al*., 2016) can be applied to predict market demand, optimize production planning, and improve inventory management. Furthermore, machine learning algorithms can analyse large datasets to identify patterns and enhance operational efficiency.

4. Ethical and social consequences of technology in greenhouse agriculture

When analysing the ethical and social impact of technologies in agriculture, it is crucial to consider aspects related to trust, freedom, autonomy, privacy, justice and equity, responsibility, transparency, solidarity and dignity (Jobin *et al*., 2019; Klerkx *et al*., 2019). The economic, social and ethical implications of such technologies can be summarized as follows.

- The existence of low-skilled labour and its costs will cease to be a decisive factor for competitiveness. On the other hand, there will be an increased need for personnel with technical knowledge. In essence, imbalances between employment supply and demand may occur (Rabobank, 2022).
- There may be less diversity in crops and increased industrial production. As some crops are more susceptible to automation than others, there is the possibility that this could reduce crop diversity. This might lead some people to reject products from a more industrial production system, affecting the consumption of such products.
- There will be greater economies of scale and organization. Automation will simplify the management of large farms, resulting in the participation of external actors in horticulture. For example, new investors (investment funds) who will see the potential benefits of an activity that reduces risk (climate, pests, etc.) due to greater control. The structure of the local economy can undergo significant changes.
- There will be increased dependency. New AI players could accelerate the end for certain traditional input providers, affecting the supply capacity of greenhouses. Horticultural farms may become highly dependent on technology providers.
- One of the most contentious points is related to privacy and security on the farm (Ryan, 2022; Wang *et al*., 2021). Large amounts of data will be collected that others can use and even manipulate in a biased and self-interested manner. There will also be increased risks related to cybersecurity. In fact, cybercrime could potentially disrupt the operation of highly technified greenhouses.

In summary, the ethical and social aspects involve: (1) the distribution of labour; (2) the modification of consumption habits; (3) the reorganization of local economies; (4) the increase in technological dependence; and (5) the loss of data privacy, as well as a reduction in security in all aspects (personal, facility-related, etc.). In this context and with the aim of ensuring a beneficial use of technology for society as a whole, while also avoiding inherent risks, legislation is necessary to regulate its application and consequences. Anticipating future scenarios will be essential to avoid outdated laws.

5. Overview of smart agriculture in southeast Spain

In this section, we review the state of technological offerings in the southeastern region of Spain (Almería, Granada and Málaga), with a focus on the province of Almería, where 88% of the total greenhouse area is concentrated (36,372 hectares among the 3 provinces). Understanding the current situation of technological offerings can help ascertain the sector's position along the adoption curve. The agri-food sector in the area is structured as a cluster, where the auxiliary industry to agriculture acts as a catalyst for incorporating innovation into the production and commercialization sector, driven by research conducted by public entities and organizations (Figure 3). Data shows that 23% of the revenue of auxiliary industry companies corresponds to services and products related to SFT (Figure 4), although the degree of innovation of these products or

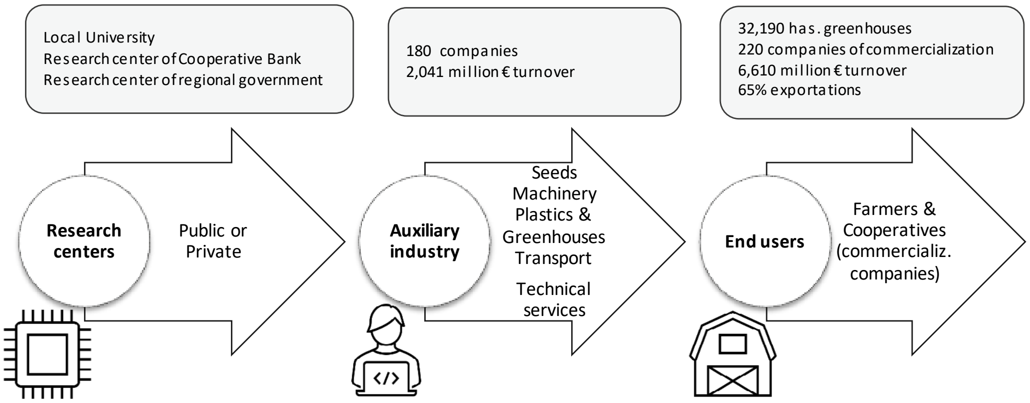

Figure 3. Composition and users of the technological cluster. Case of Almería (Spain). Own elaboration based on Cajamar (2022).

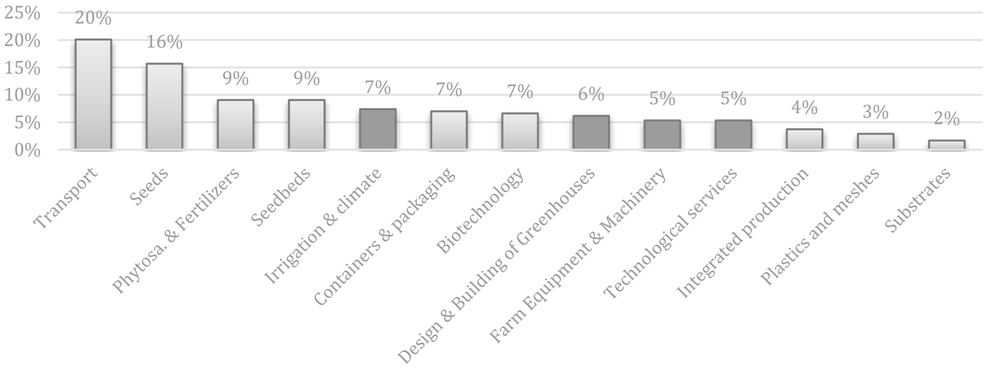

Figure 4. Percentage of turnover of the auxiliary industry to agriculture in Almeria (Spain). Darker shade, companies with the capacity to SFT supply. Source: Own elaboration based on Cajamar (2022).

services is not known. Overall, there is a very positive sectoral starting point for the future expansion of this type of technology. It is foreseeable that in the future many companies in the auxiliary industry will incorporate specific SFT lines or become users of other technological providers. Ideally, the endogenous development of a specialized industry would be desirable.

5.1 Current and future status of SFT implementation

After analysing the market it was deemed appropriate to examine the current situation of the sector regarding the adoption of technologies related to SFT. With this aim, in collaboration with the largest sectoral association of fruits and vegetables in Andalusia (APROA), a survey was prepared (conducted between September and December 2023) to determine the degree of SFT incorporation among fruit and vegetable marketing companies in the area. Data were collected from 32 companies (with a combined turnover of €2677 million and a total land area of 12 077 ha). Overall, the sample represents 40% of the sector's turnover and 37% of the area. Control data included: sales volume (Sales_Tons); turnover (Sales_€); assets (Asset); total production area (Hectar); and average area per farmer (Aver_Surf); number of members or associate farmers (Members). In this survey, company executives were asked about the following issues:

- With regard to field production: 1) percentage (%) of current use of sensors and actuators (Farm_Sensors); 2) percentage (%) of use of remote sensing, artificial intelligence, and robotics (Farm_AI).
- Regarding the handling and logistics of the company: 1) current use of remote sensing and actuators (Comp_Sensors) (yes or no); 2) use of Big Data, Cloud Computing, robots, or AI (Comp_AI) (yes or no).

Subsequently, it was requested to consider the previous questions but while aiming to anticipate the future situation in 5 years. The results can be seen in Table 1.

On the farm, the incorporation of sensors (14%) is more advanced than the use of robotic devices (which is around 5%). This situation is logical due to the complexity of incorporating the latter. However, the use of autonomous devices could multiply by five in the coming years. It should be noted that the use of robots could significantly reduce the cost of labor used on farms, which currently represents 45% of the current costs (Cajamar 2022). In companies, the use of sensors reaches 31%. In the future, this technology will be implemented in almost 60% of cases. Data analysis and the use of robots are used in 28% of companies and will become the majority in the coming years. The significant cost savings in labor (which represents 42% of the current costs of a vegetable marketing company) can be a strong incentive.

From the analysis of the correlations (Table 1), it is shown that the characteristics of the companies do not affect what happens on the farms of their partners or associates. However, there is a significant relationship between the incorporation of SFT in the companies and their size, expressed in terms of turnover (Sales_€) and average area of their farmers (Aver_Surf). This relationship also exists at the production level for the average area of farmers (Aver_Surf): larger farms are more likely to incorporate technology. These results are relevant because they indicate that companies with more investment capacity are those that will be able to cope more quickly with the changes. This situation could accelerate the polarization and differences between companies and farmers according to their size, and therefore their future viability. Modelling the survey results based on control variables corroborates the simple correlation analysis (Table 2). It is noteworthy that future models fail to achieve satisfactory adjustments. This suggests the difficulty of attempting to forecast the situation, particularly in the case of technologies characterized by a high rate of change.

Table 1. Survey results on SFT implementation in fruit and vegetable marketing companies and correlation among variables.

	Farm_ Sensors	**Farm_ Sensors 5 years ahead**	**Farm_AI**	**Farm_AI 5 years ahead**	**Comp_ Sensors**	**Comp_ Sensors 5 years ahead**	**Comp_ AI**	**Comp_AI 5 years ahead**
Average/%	14.6	45.8	4.7	19.1	31%	59%	28%	53%
Desv. Tip.	7.5	17.3	4.1	9.7				
Sales_Tons	−0.086	0.200	0.385*	0.138	0.551**	0.315	0.605**	0.133
Sales_€	−0.093	0.188	0.378*	0.126	0.591**	0.332	0.650**	0.142
Asset	−0.038	0.131	0.266	0.156	0.481**	0.350*	0.472**	0.196
Hectar	−0.076	0.209	0.387*	0.131	0.555**	0.307	0.609**	0.122
Members	−0.240	0.220	0.188	0.056	0.505**	0.322	0.573**	0.069
Aver_Surf	0.864**	0.073	0.589**	0.041	0.201	−0.172	−0.078	0.064

n=32. For qualitative variables, Spearman's rank correlation coefficient is used.

* The correlation is significant at the 5% level; ** the correlation is significant at the 1% level. Source: Own elaboration.

Table 2. Estimations with OLS and binary logistic model.

	OLS (standardized coefficients)				**Binary logistic model**			
	Farm_ Sensors	**Farm_ Sensors 5 years ahead**	**Farm_AI**	**Farm_AI 5 years ahead**	**Comp_ Sensors**	**Comp_ Sensors 5 years ahead**	**Comp_AI**	**Comp_AI 5 years ahead**
Intercept					−5.462	−0.388	−2.616	−0,713
Sales_€	−0.362	−1.216	0.347	−0.044	0.089*	0.040	0.119*	0.031
Asset	0.236	−0.202	−0.346	0.162	−0.001	0.006	−0.015	0.007
Hectar	0.185	1.266	0.711	0.319	−0.016	−0.009	−0.016	−0.007
Members	0.052	0.397	−0.276	−0.318	0.007	0.005	−0.002	−0.002
Aver_Surf	0.888**	0.172	0.622**	0.005	0.552**	−0.038	−0.103	0.088
R^2 ajust./R^2 N	0.720	0.332	0.550	0.140	0.660	0.271	0.666	0.128
HandL					10.461	6.419	9.199	4.386

n=32. Only variable Sales_€ is included due to its strong correlation with variable Sales_Tons. R^2 N= R^2 of Nagelkerke; HandL= Chi-Square Hosmer and Lemeshow.

* The correlation is significant at the 5% level; ** the correlation is significant at the 1% level. Source: Own elaboration.

6. Gathering experts' opinions about sustainability

6.1 Methodology

Regarding the first stage of data collection in this study, the aim is to gather the opinions of individuals with experience in implementing innovations in the greenhouse horticulture sector in southeast Spain, which is considered a key area for horticultural production and trade in the EU. These experts not only have in-depth knowledge in their specialized areas but can also provide critical insights as well as identify emerging trends and innovative approaches that may not have been formally documented. The combination of a literature review and expert interviews not only strengthens the rigor of this investigation, but also provides a more comprehensive and balanced understanding of the studied topic, thereby enriching the insight into the phenomenon at hand.

In the initial stage, 10 semi-structured interviews were conducted with individuals who have a high level of knowledge about technology. These individuals have PhDs and post-graduate degrees and work in prominent organizations in the sector (Table 3). The first part of the interviews involved a guided conversation to gather qualitative information related to technologies associated with smart farming. Participants were asked which technologies currently have the most significant impact on greenhouse agriculture and which are expected to play a predominant role in the coming years. In addition, participants were questioned about the pace of implementation of these technologies, whether it was rapid or more gradual. The fundamental part of the interview focused on the impact of technological development on sustainability, primarily within the greenhouse production phase. However, as the interviews progressed, it became clear that experts emphasized the downstream impact of smart farming on the manufacturing and commercialization stages of the product. This led to further exploration of this aspect of the value chain, which ultimately resulted in differentiated responses.

For the collection of information, qualitative data analysis techniques were applied. The use of qualitative techniques has become more popular and acceptable in recent decades among researchers (Nazmy, 2016). The use of qualitative techniques depends on the concept and objectives of the research, as well as the types of information needed to achieve objectives (Hutchison *et al.*, 2010). Of course, as a preliminary stage, it will be necessary to define a theoretical position. As this framework is already defined, the standard phases

Table 3. Characteristics of the experts interviewed.

	Professional profile	Academic profile		Professional profile	Academic profile
1.	Manager of an auxiliary agriculture company	Postgraduate Studies	2.	Technical Field Manager of a cooperative company	Ph.D.
3.	Manager of an auxiliary industry association	Ph.D.	4.	Farmer and Field Technician	Postgraduate Studies
5.	Manager of the largest cooperative company in the region	Postgraduate Studies	6.	Farmer and Quality Manager at a Cooperative Company	Postgraduate Studies
7.	Manager of the association of cooperative companies	Ph.D.	8.	Farmer	Graduate Studies
9.	Farmer	Postgraduate Studies	10.	Technical Manager in a Cooperative Company	Graduate Studies

Source: own elaboration.

of this methodology involve (Akinyode and Khan, 2018): Data Logging, Research and Deepening into Analysis Units or Themes, Data Coding, and Thematic Network. (1) Data logging is the process by which raw data from the personal interview is recorded in writing. The process is also known as data documentation. (2) Research on analysis units where basic themes are formed. The researcher must transcribe the anecdotes that the interviewee shares, summarizing the narrative explanation in an organized sequence and subdividing the captured themes into other dimensions, if necessary. (3) Coding is the procedure for fragmenting themes to obtain a complete explanation of the issue. Fragmentation can be organized according to paragraphs, phrases, or keywords. (4) Thematic network aims to represent the main ideas; it is an organizational system that seeks to find the fundamental themes and subsequently attempts to interpret them. This involves combining two or more basic themes into an "organizing theme".

The second part of the interview involved the application of a questionnaire to extract the weighting of the positive and negative impacts that smart agriculture has on economic, social, and environmental sustainability from experts. For this purpose, the Analytic Hierarchy Process (AHP) methodology was applied. Following Saaty (1980), the weighting of attributes (w_t, where t=number of variables/questions used, in our case 24) is obtained based on pairwise comparisons. Saaty proposes a scale from 1 to 5 (1 equivalent to a similar importance between both attributes, while 5 represents an absolute supremacy of the first attribute with respect to the second). In our case, for each respondent, a matrix was generated that compares the importance of each variable with each of the others (Table 4).

The calculation of the individual weights assigned by each respondent to the different attributes was carried out using the geometric mean, since the literature (Fichtner, 1986) does not find any evidence of the absolute superiority of using other systems. As a final step, all the information provided by the respondents (h) must be summarized. Although the AHP technique was designed for individual decisions, it was later generalized for group decision making (Easley *et al*., 2000).

Given the complexity of conducting this type of survey, where the interviewee must make 276 comparisons, it was decided to provide a prior explanation of the survey and apply it to only 3 respondents.

6.2 Research and in-depth study of the fundamental units or themes of analysis

Having completed the data logging phase, in which the interviews were summarized and standardized based on the theoretical questions explored, we proceed by shaping and delving into the units of analysis, which had to be theoretically defined, at least in a general way, to facilitate the interviewer's work. In the present

Table 4. Saaty matrix for each respondent

Variable	***R*1**	***R*2**	**…**	***R*24**
*R*1	$a_{1,1}=1$	$a_{1,2}=(1/a_{2,1})$	…	$a_{1,15}=(1/a_{24,1})$
*R*2	$a_{2,1}$	$a_{22k}=1$	…	$a_{2,24}$
…			1	
*R*24	$a_{24,1}$	$a_{24,2}$	…	$a_{24,1}=1$

Source: Own elaboration.

case, firstly, a general summary of the extracted information is presented, which was organized into common elements for all interviewees as far as possible. In summary, the aim is to extract which issues are most relevant to the interviewees, who seeks to focus the conversation on the previously set objective, which, in our case, is the impact of smart agriculture on the value chain of greenhouse horticultural production in aspects related to sustainability. The aim is to extract the most relevant questions, phrases and ideas related to the topic to be analysed.

Regarding the disruptive or incremental nature of technologies, respondents are clear that technologies are having a radical impact, yet in sectors such as agriculture, especially in activities such as greenhouse cultivation, their application is more gradual. The latter owes to the lack of technological training among farmers, primarily due to their older age, which acts as a limiting factor, and due to the small size of agricultural holdings. They also believe that: "Technologies will change business models in agriculture and in the commercialization activity. In any case, the companies have had to adapt to the changes as something natural, it doesn't scare us either, it is something we are used to. In fact, this area has experienced a radical change in cultivation systems in the last 20 years, just think of what has been done since the introduction of integrated pest management ".

When asked which technologies are currently having the greatest impact, the response is consistent and clearly in favour of IoT (Internet of Things) and sensorization, mainly in harvesting and in the field. Additionally, they also cited AI (Artificial Intelligence) as a unifying element in the use and exploitation of data is a common response. In contrast, technologies like blockchain or robotics are considered to have: "Not taken off or started yet, so there is still much to do and develop […]. I don't think you have to go overboard with very complicated technologies. Sensorization will certainly optimize irrigation or fertilization, but I also think that by introducing simple rainwater harvesting systems, we can save up to 15%–20% of what the farm needs […]. Also, don't forget what these systems are going to cost us and what we can save with them.". Two out of the seven respondents stated that biotechnology is the most important framework currently: "Imagine what can be done with the inclusion of CRIPSPR. You can have drought-adapted, pest-adapted plants that need less care and therefore less labour. It will be a real revolution"

If we focus on future prospects, the technologies that will have the greatest impact are undoubtedly AI and IoT. One of the respondents specified their answer further, arguing that all efforts should be directed towards "a technology that allows finding a new source of clean, cheap, abundant energy and that allows replacing energy from fossil elements[…]. This would affect the entire agri-food chain.".

When asked about which phase of the plastic greenhouse crop supply chain will experience the greatest impact from automation of agriculture (production, handling and packaging, marketing, distribution and logistics), the most common response is that AI will have a greater impact on marketing activities. Meanwhile, in production, IoT and sensorization are seen as technologies with more future potential. Not so favourable opinions were also found: "There is a lot of talk about AI. However, it remains to be seen how we can adapt it. Some things are seen to be useful, others not so much".

The interviews reach a crucial point when asking about the relationship between smart agriculture and sustainability in its three dimensions (economic, environmental, and social). The responses varied. One respondent did not differentiate, emphasizing that "the three aspects are interrelated and are communicating vessels." Other respondents state that, undoubtedly, the environmental dimension will be the most affected, since climate change and efficient use of water (water footprint) are issues addressable from this perspective. Finally, others emphasized the economic and social aspects of these technologies: "What I am interested in is that the technology gives me an advantage over the competition, for example, by reducing my dependence on labour, either in the field or in handling.".

Respondents were asked to provide specific examples of how the use of these technologies can impact different dimensions of sustainability, differentiating between the greenhouse production phase and the handling, marketing, and logistics phase. The interviewees proposed a series of specific situations which are summarized below.

(1) Greenhouse production phase:

- IoT and sensors will be used to reduce inputs, such as water or fertilizers, with a particular emphasis on reducing environmental impact on soil.
- AI and image processing will increase crop productivity and efficiency, aiding in pest control, and improving fruit quality. This will impact the sustainability of economic and environmental resources.
- Collaborative projects with companies, involving sensorization and data analysis, aim to develop algorithms for optimal irrigation proposals, resulting in a high environmental impact.
- IoT, sensors, AI, and image processing will have an impact on the reduction of waste in daily management.
- Sensorization and automation will be useful in reducing energy and water consumption, with an acceleration in the adoption of these systems.
- Drones, once equipped with a cheap, abundant and clean energy source, will play a significant role in the greenhouse, such as in preventing disease through image analysis.
- The consideration of technology extends to innovations such as the use of multifunctional plastics to generate electricity through photovoltaic cells, thereby reducing energy costs in the field.
- Technology will improve the well-being and quality of life of agricultural workers. Robotics, especially in fruit harvesting, will improve farmers' living standards, albeit with ethical implications due to the replacement of manual labor.
- The use of technology has reduced the hardship of labor, and robotics will replace and assist in the toughest agricultural activities, leading to improved working conditions for workers.
- Technology has historically caused social disparities. Training for the adoption of new technologies is crucial; those who cannot adapt may face challenges. The social impact will be significant.
- New technologies will facilitate the implementation of other innovations or cultivation methods, such as biological pest control or even organic production. They will also influence biotechnology, such as developing seeds that use water efficiently or genetically modified seeds to increase pest resistance.

(2) Handling, commercialization, and logistics phase:

- Robotization is already influencing operations in fruit and vegetable marketing companies, with time savings and reduced labor being a reality. The economic and social dimensions will be most affected.
- AI, cloud computing, and Blockchain will facilitate communication coordination between suppliers and clients, aiding real-time information exchange for shipment scheduling and choice of transportation systems. Process optimization will result in significant cost savings.
- Improvements in AI in supply (variable in the agricultural sector) and demand forecasting will improve productivity and reduce waste.
- IoT will improve energy optimization in facilities, even in logistics, helping to discriminate routes and intermodal systems based on effective energy consumption between origin and destination (optimization of the CO2 footprint). The environmental dimension will be the most affected.

- Technification, in general, will help innovation in energy usage reduction in handling plants and implementing cross-cutting technologies, such as photovoltaic energy.
- Implementing business intelligence systems will optimize all processes, save costs, and enhance productivity.
- The dependence on technology providers, and the use they can make of the generated data can prove worrying. Companies are becoming more and more technified. Clear regulations and criteria will have to be established regarding the ownership and use of the information generated.

6.3 Fragmentation of topics into terms/keywords: relationships between them

In the analysis of conducted interviews, a concept cloud was generated to highlight the most frequently used words (Figure 5). The initial observation indicates a positive impact of these new technologies, especially in the production phase, with notable improvements in inputs, primarily water. Additionally, the social impact of technology assisting in daily tasks is also highlighted. With regard to the most mentioned technologies, sensors and the use of images stand out. There is also a need to improve data collection to refine models for input control.

Upon close examination, social and environmental dimensions appear to be the most affected, while the economic benefit may not be as evident. In the manipulation, commercialization, and logistics phases, emphasis is placed on improvements in communication and coordination between suppliers and customers. Environmental issues, particularly energy savings, play a significant role (a fundamental cost in these stages of the chain). Unlike in the production phase, the impact on cost reduction is much clearer, making the economic dimension crucial for implementation. The technologies mentioned above refer to the automation of processes.

A matrix of relationships is thus constructed, which ultimately aims to identify groups according to the dimensions: technology-impact-sustainability. The following are used as key terms: (1) the most frequent words mentioned above related to specific impacts (water, energy, time, optimization, work, cost, waste, fertilizers, ethics/data/dependence); (2) sustainability (environmental, social, and economic); and (3) the most used technologies. Using MAXQDA software, we can review each concept one by one for each interview and relate it to the rest to create a frequency matrix. In practical terms, codes are assigned to the text segments representing the units of analysis. In the first phase, codes are assigned to the paragraphs, for each transcribed interview, that talk about (1) type of sustainability; (2) then the different impacts are identified within them; (3) the same is done with the type of technology. Once the text is coded, a matrix is generated where the rows and columns represent the codes, and the cells show the frequency of co-occurrence of the codes.

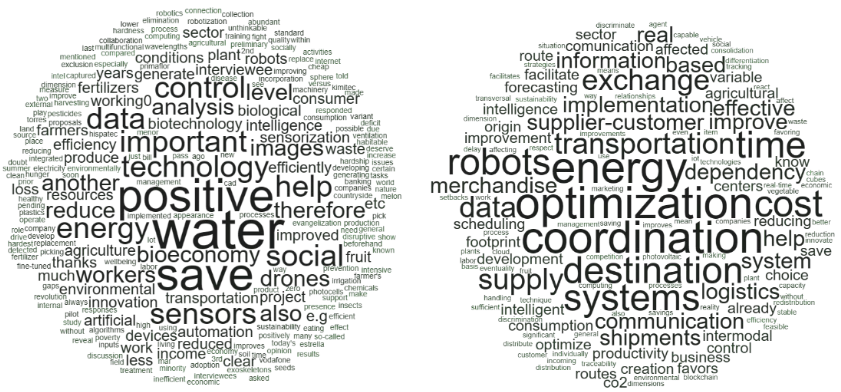

Figure 5. Cloud of words most used in the interviews. Source: own elaboration.

Subsequently, we proceed with the detection of term communities using the modularity algorithm developed by Blondel *et al*. (2008) through the Gephi software. This is one of the most popular methods for detecting community structures in complex networks by optimizing their modularity (Q), which is the measure that assesses the quality of a network partition into meaningful groups. A high Q suggests that there are many connections within communities and few connections between them, which is desirable for a good community partition.

The analysis of communities allows us to extract interesting results (Figure 6): (1) There is a significant relationship between environmental sustainability and the improvement in water and energy management, with IoT sensorization being the fundamental technology in this regard. (2) Economic sustainability has a strong connection to the social dimension. Both focus on input savings but mainly labor. In this aspect, robotics will be the optimal technology, as well as any other type of autonomous mechanization that generates time savings. (3) A key aspect worth considering is that ethical issues related to data management or technological dependence fall outside the scope of sustainability. However, the strongest relationship occurs with social sustainability and variables related to labor management, the use of robots, and the generation of sensitive information through sensors. In the ethical realm, the technology that raises the most concern is the use of AI. In terms of relative importance, environmental and economic sustainability are fundamental dimensions. Regarding technologies, the use of sensors stands out, proving much more relevant than the use of robots or other types of machinery.

In the creation of communities, the context in which certain words are cited must be considered when creating the matrix of relationships: this implies that although there are relationships that can be considered more direct (e.g. “cost” and “save”; or “cost” and “worker”), these are implied by the existence of other stronger relationships.

The weighting survey (Table 5) serves to qualify and complete the analysis of relationships. In general terms, in this order, economic and environmental sustainability (both almost equally), and to a lesser extent, social

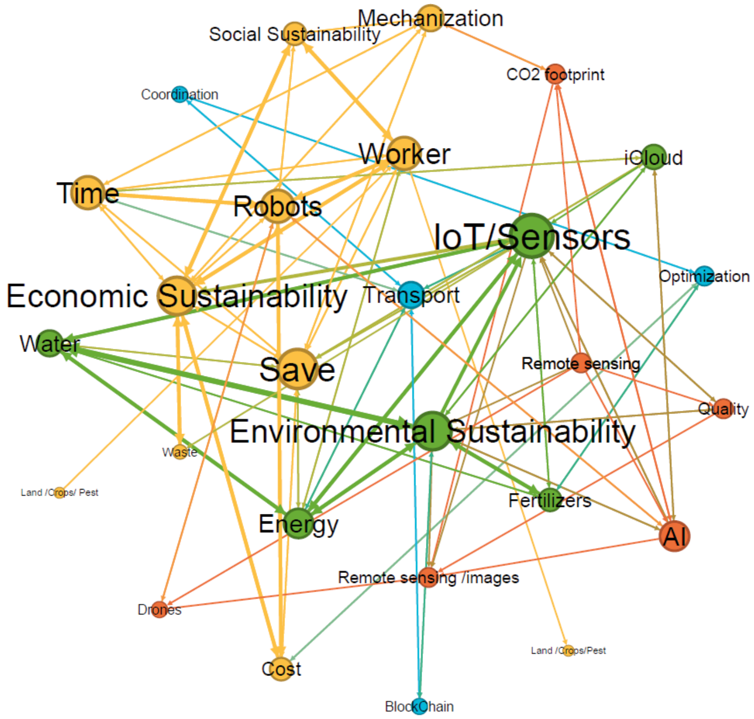

Figure 6. Communities of concepts identified. Source: own elaboration.

Table 5. Results of the impact weighting Saaty survey.

	Environ.	Econ.	Social/Ethics	
Field production				52.0%
Sensors and actuators reduce/optimize water consumption.	7.6%	6.8%	2.6%	17.0%
Sensors and actuators reduce/optimize energy consumption.	6.8%	4.9%	2.3%	13.9%
Sensors and actuators reduce/optimize fertilizer usage and, in general, their impact on the soil.	3.6%	2.6%	3.1%	9.2%
Remote sensing, artificial intelligence (AI), and robotics facilitate harvesting tasks.	3.1%	3.3%	5.4%	11.8%
Handling and commercialization				48.0%
Remote sensing, artificial intelligence, and robotics facilitate tasks.	4.7%	5.0%	4.3%	14.0%
Big data, cloud computing, and AI improve internal management.	3.7%	3.7%	5.0%	12.3%
Big data, cloud computing, and AI improve commercial tasks, including transportation.	4.5%	5.0%	3.0%	12.4%
Big data, cloud computing, and AI improve collaboration and communication within the supply chain.	2.3%	4.7%	2.2%	9.2%
Total	36.3%	35.9%	27.8%	100%

Source: own elaboration.

sustainability, will be the dimensions most affected by the application of smart agriculture. Of all technologies, the use of sensors in water management in the field will be the most predominant technique, with significant positive implications for the environment; however, it will not have an equivalent economic impact. The impact of robotics on the handling of fruits and vegetables in cooperatives/commercialization companies stands out, mainly due to its potential for cost savings. Third, sensor technology applied to energy reduction in the production phase will have a positive environmental impact but a less economic one. The potential social/ethical impact of AI on the internal management of companies is noteworthy, given the existence of highly sensitive data in this domain, which requires protection. In general terms, the production phase will be the most affected by the application of smart agriculture, although, as we have seen, there are important aspects to consider.

7. Discussion and conclusions

The current study addresses contemporary challenges in agriculture, proposing agricultural digitization as a variable solution. The research specifically focuses on intensive greenhouse agriculture in southeast Spain, highlighting its importance in European horticultural production. In relation to this specific sector, a favourable starting point is observed regarding the incorporation of SFT. The sector's own cluster-like structure and the presence of a robust auxiliary industry to agriculture make it feasible for the utilization of these technologies to rapidly expand in the coming years. This is also evident when considering the opinions of the experts in the marketing companies.

On the other hand, the main goal of the study was to analyze the impact of smart agriculture and precision technologies on sustainability, considering environmental, economic, social, and ethical aspects. The investigation delves into both the agricultural production phase (farmer) and the preparation for marketing at the source (trading company).

The analysis reveals the significant impact of these technologies, especially in reducing inputs, improving efficiency, and optimizing processes. Concerns regarding dependence on technology providers and the ethical management of generated data are briefly addressed. A detailed analysis of expert interviews provides important information on the impact of technology on sustainability.

The results identify three key clusters with interrelated factors. The first cluster relates to fieldwork, water savings, sensor use, and environmental improvement. The second addresses aspects pertaining to the cooperative company, including the adoption of robots, labour reduction, and subsequent improvements in cost efficiency and economic sustainability. The third, although of lesser importance, links artificial intelligence to ethical considerations, encompassing issues such as data control and utilization, and technological dependence.

In summary, the application of smart agriculture will positively impact economic and environmental sustainability, with subsequent implications for the social dimension. It seems that social and ethical aspects would be relegated to the pursuit of more immediate benefits, particularly in the realms of environmental and economic gains. This issue is relevant, as the implicit acceptance of data sharing and technological dependence would occur if more tangible results were achieved. From a strategic point of view, this poses challenges that highlight the need to adopt proactive attitudes to reshape the sector's perspective on this issue. Specifically, among the technologies analysed, the use of sensors for water management in the field is identified as the most relevant, with significant environmental benefits, yet with a more limited economic impact. The implementation of robotics in the handling of fruits and vegetables in cooperatives and other marketing companies is notable, given its potential cost savings. These results are consistent with those of authors who suggest that advances in available technologies have greater acceptance in solutions with short-term effects (e.g., irrigation control). However, when they require significant investment with medium to long-term benefits (e.g., robotics and artificial intelligence), the current progress appears to have a less immediate impact (Kernecker *et al*., 2020; Long *et al*., 2016).

The use of sensors to reduce energy in the production phase is perceived to have a positive impact on the environment, although it is less pronounced in economic terms, leading to limited adoption in agricultural operations.

The implementation of remote sensing or the use of robotics in the harvesting phase is currently not widespread but holds potential. In the case of southeast Spain, these technologies would prove valuable in addressing competition from other low-cost production areas. They could have a positive impact on reducing labour costs, a critical factor where a significant gap exists compared to the most important competitors, such as Morocco or Turkey. Adapting the greenhouses to facilitate robot operations on the farm, as well as enhancing the precision of the robots in specific tasks, such as fruit picking, would be necessary for the successful implementation of these technologies.

Users perceive an excessive cost associated with the technological solutions to be implemented (Klerkx *et al*., 2019), both in terms of hardware with sensors and actuators, as well as in software applications. As some of these advancements gain popularity in other industries, their development costs may decrease (European Commission, 2017).

The still nascent application of some technologies, such as artificial intelligence, to enhance the performance of intensive agricultural operations means that data ownership issues may currently take a back seat for the surveyed population. However, it could become more significant as the potential of these technologies is further exploited (Jobin *et al*., 2019; Ryan, 2022).

From a management perspective, the future investment requirements could lead to polarization within the sector. In other words, not all farmers and companies may be able to cope with the investments necessary to maintain future competitiveness, potentially resulting in a gradual deterioration or even abandonment of the activity due to technological lag (Reichardt and Jürgens, 2009). The technological monitoring of companies in the sector can be carried out through agricultural engineers and cooperative marketing companies, which can act as prescribers or disseminators. The literature recognizes them as essential elements in the diffusion and importance of smart agriculture (Hoste *et al*., 2017).

The study presents limitations primarily associated with the exploratory nature of the work and the scope of the fieldwork. Data have focused on a specific area in southeast Spain where the level of technification is high and respondents belong to a group with advanced technological development, as evidenced by their participation in research projects on technification (García Granero *et al*., 2020). This bias probably reflects future trends in the sector rather than the current state. Extending fieldwork to include less advanced farmers and respondents with educational backgrounds higher than the sector average would facilitate a comprehensive mapping of technology application in the sector. In addition, the results obtained by correlation analysis may lack robustness due to the use of a small sample size. The study of the actual implementation of these technologies on intensive farms and the expansion of the number of surveys used to improve quantitative research are pending for future research works.

In summary, this work has highlighted that the current contributions of smart agriculture in the greenhouses of southeast Spain, primarily targeting efficiency in input utilization, particularly water, with consequential environmental and economic impacts. However, notable challenges persist in streamlining labour-intensive tasks associated with crop monitoring, harvesting and post-harvest.

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