The technological translation from Industry 4.0 to Precision Agriculture: adoption and perception of Italian farmers

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Abstract:
Purpose:
This research aims to identify the rate of knowledge, adoption and perceptions of Italian farmers towards Precision Agriculture technologies.
Methodology:
An online survey was carried out, using the Snowball sampling method, among 755 Italian farmers and involving the main Italian trade associations.
Findings:
The findings showed that among Italian farmers the technologies related to *Monitoring* appear to be the best known, adopted and perceived as the most useful; followed by technologies related to *Automation* and *IoT*.
Managerial implications:
Considering the results that emerged from this research, it seems necessary to undertake models of training development paths so that farmers can deepen the themes of technological integration with an orientation towards sustainability.
Research limitations:
The present research, not being able to be considered exhaustive for the understanding of the phenomenon, aims to be the starting point for future research aimed at a further analysis on the models of diffusion and technological integration.
Originality:
The models of technological integration for agricultural cultivation techniques are constantly evolving. Through the analysis of knowledge, use and perception of farmers it could be possible to detect new models for the diffusion of technology.

Keywords: Precision Agriculture; Industry 4.0; Digital Transformation; Agricultural technologies.

1. Introduction

In recent years, the fundamental role of new technologies within innovation processes has developed in companies all over the world (Granstrand and Holgersson, 2020; Nambisan et al., 2019). This new trend is sublimated by the wave of the Industry 4.0 paradigm and the agricultural sector is not exempt from it (Boursianis et al., 2022; Sundmaker et al., 2016). This fourth industrial revolution is ongoing and is characterized by the fusion of new interconnected emerging technological domains. The very integration between Industry 4.0 and the agri-food sector is playing a key role for companies in strengthening production processes and organizational structures through new technological domains such as automation, interconnection and data exchange (Liu et al, 2021). The interest in the modernization of the agricultural system does not come from farmers but is under the focus of interest of various players on the global scene. To motivate the growing attention, it is necessary to point out the world situation on food availability

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in relation to the population which in the year 2022 exceeded 8 billion people (UNFPA, 2023). Furthermore, the joint FAO, IFAD, UNICEF, WFP and WHO report entitled "The State of Food Security and Nutrition in the World 2022" points out that the number of people suffering from hunger worldwide has risen to as many as 828 million in 2021, or about 46 million more since 2020 and 150 million more since the outbreak of the COVID-19 pandemic (FAO, IFAD, UNICEF, WFP and WHO, 2022). Therefore, it seems necessary to focus on how global agri-food systems can support the essential needs of the world population, since both developing and emerging countries need to optimally satisfy quantities of food and at the same time the populations of industrialized countries have specific nutritional needs. In this regard, the adoption and development of modern technologies within agricultural production systems have led, in recent years, to a significant improvement in terms of performance and productivity for almost all types of agricultural crops, supporting farmers in the entire management and decision-making phase of the production process (Elijah et al., 2018). The dissemination of knowledge and the subsequent diffusion of Precision Agriculture (PA) technologies is constantly growing within the global and European panorama, although several improvements seem to be possible. The global market of the Precision Agriculture appears to be in constant expansion, in 2017 it was worth just under 10 billion dollars, in 2022 it exceeded 23 billion dollars, recording a growth of 13.5% by 2025 in Europe, 15.7% in Asia, 12% in North America and 16% in South America (Statista, 2022). Within the Italian context, in a few years the technological market linked to the technological implementation in agriculture and Precision Agriculture has had a constant improvement, passing from the use of Precision Agriculture technologies on 1% of the total surface agricultural used in 2017 at 6% in 2023 for which it is worth 1.6 billion euros in the national market (Osservatorio Smart Agrifood, 2022).

2. Precision Agriculture: definitions and distinctive elements

Starting from a literature review carried out on the Scopus database (see Table 1.1) focused on the analysis of definitions of the concept of Precision Agriculture, it emerged that technology was the first central element of Precision Agriculture. However, over the years the attention of the scientific community has also focused on other elements, such as: General Benefits, Sustainability and Applications. This development path can be seen in Table 1.1, where the definitions of Precision Agriculture is represented over time, has been an evolution of the various provisions of the PA that have slowly allowed to establish the constitutive elements of the concept and its fields of application in order to intercept, among other things, the PA as a management tool alongside with concepts of economic and environmental sustainability.

Table 1.1. Literature review, definitions, and distinctive elements of Precision Agriculture. Source: elaboration on Tarabella et al., 2019.

AUTHOR	**DEFINITION**	**TITLE AND JOURNAL**	**YEAR**	**DISTINCTIVE ELEMENTS**
F.J.Pierce, P. Nowak	Precision agriculture is the application of technologies and principles to manage spatial and temporal variability associated with all aspects of agricultural production for the purpose of improving crop performance and environmental quality.	Aspects of Precision Agriculture- Advances in Agronomy vol. 67, pp. 1-85	1999	Technology Generated Benefits

AUTHOR	DEFINITION	TITLE AND JOURNAL	YEAR	DISTINCTIVE ELEMENTS
H. Kirchmann, G. Thorvaldsson	Precision agriculture is a discipline that aims to increase efficiency in the management of agriculture. It is the development of new technologies, modification of old ones and integration of monitoring and computing at farm level to achieve a particular goal.	Challenging targets for future agriculture - European Journal of Agronomy 12, pp. 145–161	2000	Technology Generated Benefits
J. V. Stafford	Precision Agriculture is "information intense" and could not be realized without the enormous advances in networking and computer processing power. Precision Agriculture, as a crop management concept, can meet much of the increasing environmental, economic, market and public pressures on arable agriculture.	Implementing Precision Agriculture in the 21st Century Jagric. Engng Res 76, pp. 267-275	2000	Technology Generated Benefits
N.Zhang, M.Wang, N.Wang	PA is conceptualized by a system approach to re-organize the total system of agriculture towards a low-input, high-efficiency, sustainable agriculture.	Precision Agriculture-a worldwide overview Computer and Electronics in agriculture, 36, pp. 13-132	2002	Technology Generated Benefits Sustainability
R. Bongiovanni, J.Lowenberg-Deboer	Precision Agriculture (PA) can help in managing crop production inputs in an environmentally friendly way.	Precision Agriculture and Sustainability Precision Agriculture, Vol.5, pp.359–387,	2004	Sustainability
A. McBratney, B. Whelan, T. Ancev, J. Bouma	One generic definition could be ''that kind of agriculture that increases the number of (correct) decisions per unit area of land per unit time with associated net benefits''.	Future directions of Precision Agriculture - Precision Agriculture, 6, pp. 7-23 Springer Science Business Medis Inc.	2005	Generated Benefits
Y. S. Tey, M. Brindal	Precision agriculture is a production system that involves crop management according to field variability and site-specific	Factors influencing the adoption of precision agricultural technologies: a review	2012	Technology

AUTHOR	**DEFINITION**	**TITLE AND JOURNAL**	**YEAR**	**DISTINCTIVE ELEMENTS**
	conditions. Precision agricultural technologies are those technologies which, either used singly or in combination, as the means to realize precision agriculture.	for policy implications, Precision Agriculture, Vol.13, pp 713-730		
E. Pierpaoli, G. Carli, E. Pignatti, M. Canavari	Precision Agriculture is a fairly new concept of farm management developed in the mid-1980s. PA bases its applicability on the use of technologies to detect and decide what is "right".	Drivers of Precision Agriculture Technologies Adoption: A Literature Review, Procedia Technology, Vol.8, pp.61-69	2013	Farm Management Technology
R. Schrijver, K.Poppe, C. Daheim	Precision agriculture (PA) or precision farming, is a modern farming management concept using digital techniques to monitor and optimize agricultural production processes.	Precision Agriculture and the future of farming in Europe- Scientific Foresight Study	2016	Digital techniques
International Society of Precision Agriculture (ISPA)	Precision Agriculture is a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production	International society of precision agriculture (ISPA). https://www.ispag.org	2019	Management Strategy

Table 1.1 shows how in the literature there a gradual transition has been starting from the management approach from considering Precision Agriculture as an application (Pierce and Nowak, 1999) to Kirchmann and Thorvaldsson (2000) which define it as a discipline to achieve a particular goal. Stafford (2000) describes it as an "information intense" while Zhang (2002) introduces it as a system approach, up to the definition of Tey and Brindal (2012) who frame it as a production system. In more recent years, starting from the studies of Pierpaoli et al., (2013) it is possible to notice a different approach to the Precision Agriculture paradigm that goes from being considered a mere application of agricultural practices to a "new concept of farm management".

This new approach can also be seen in the European study published by Schrivjver et al. (2016) where it is presented as a "modern farming management concept" up to the more complete definition provided by ISPA (2019) where Precision Agriculture is defined as "a management strategy".

3. Technology and Agriculture: beginning and evolution of Precision Agriculture

From a technological point of view, the beginning of Precision Agriculture could be identified up to the openness by governments in the use of military satellites for civil use, with the introduction of GPS as a general-purpose technology (see Figure 1.1). It was possible to reach a technological level that allowed to establish the precision in the execution of all field activities with a very high level of precision in site-specific management. The goal of those new techniques is to remodel the necessary interventions (as far as space and time are concerned) in the best possible way, to optimize the results of the production process in both economic and environmental terms.

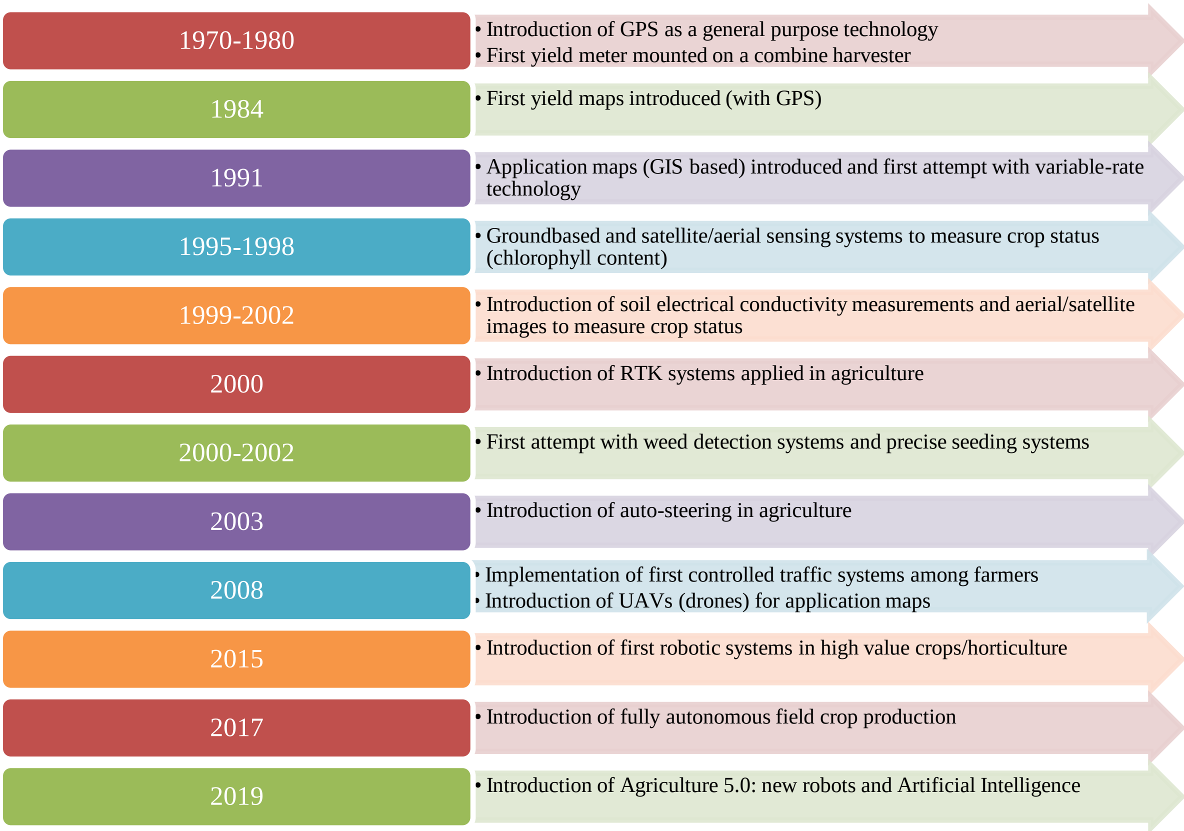

Figure 1.1. History of Precision Agriculture. Source: elaboration on Pedersen and Lind, 2017

Early enabling technologies in PA include, as mentioned above, the Global Positioning System (GPS) but also Geographic Information Systems (GIS) and a multitude of different sensors to assess site and crop variability, providing accurate information to assist growers in managing agricultural system. The rapid technological advances that have taken place since the mid-1990s (as can be seen from Figure 1.1) in Information and Communication Technology (ICT) systems, robotics and global positioning systems, are currently enabling the development of a suite of PA technologies that promise to deliver sustainable, high-productivity farming systems. PA technologies have enormous potentials that can bring a new wave of increase in agricultural productivity and can contribute to the environmental sustainability of the agricultural systems. In fact, in 2019, as shown in Figure 1.1, it arrives the new concept of Agriculture 5.0, which proposes the use of equipment that involves autonomous decision support systems using new robots and some forms of Artificial Intelligence (Saiz-Rubio and Rovira-Mas, 2020). However, it must be clear that the application of sensor technology or electronics is not sufficient to speak of Precision Agriculture, given that its employment is independent from the use of these technological applications. The mere computerization of some agricultural processes or the introduction of sensor technologies alone do not mean that is possible to speak of Precision Agriculture. Precision Agriculture is the application of all these technologies and the integration between them to manage the spatial and temporal variability associated with all aspects of agricultural production with the aim of improving efficiency and reducing its environmental impact. This development is simplified by help of smart technologies that nowadays are represented by devices that have entered the daily life of modern man. Suffice it to say that in 2022, the Internet diffusion rate among households residing in Italy with at least one member aged 16-74 was 91.4%, a value in line with the EU27 average (92.5%) (Istat, 2023). The use of internet can currently be used to apply Precision Agriculture technologies in agricultural crops and that allows farmers to gain detailed information about their fields and subsequently to treat them accordingly (Michels et al., 2020). Furthermore, Precision Agriculture can be used as an integral management system where the control of agricultural applications, data recording and the operations of analysis and business planning meet. Within the company information system, it starts from the acquisition of raw data through Precision Agriculture technologies such as systems and sensors useful for data collection. The raw data is then processed thanks to models and decision support systems for business decisions, that allow the increase of knowledge by entrepreneurs and decision makers for a correct evaluation of the data. These data will then be entered into the communications systems and transferred within the company, used for control and decision functions. These management information systems have in fact a dual function, both to support the entrepreneur in the management of structured problems and to support the management of unstructured problems. As regards the support function in the management of structured problems, the monitoring and documentation activities help in the collection and availability of information relating to the production context, useful both for information for certifications or functional checks and for increasing the automation of processes. For the management of unstructured problems, i.e. non-standardized or non-automatable, the collected data can be used in interactive simulations that include possible alternative scenarios and that can offer comparative assessments of their behaviour, an essential function in an agricultural context where there are strong randomness components in the planning of events and operate in open spaces, subject to weather changes.

4. The sublimation of Industry 4.0 in agriculture: identification of technological clusters

Currently, study models are being studied to uniquely unify industry 4.0 technologies in the public administration landscape to achieve a series of objectives:

- Clarify what is useful and applicable for businesses;
- identify which tools of industry 4.0 are most widely used;
- identify policy tools to finance virtuous businesses.

For example, the University of Pisa carried out a study by developing a dictionary which identifies the most innovative technologies that are applied in Precision Agriculture by investigating the overlaps with Industry 4.0 technologies to create clusters and to analyze the connections between them (Trivelli et al., 2019). The dictionary aims to analyze the technologies related to the Precision Agriculture domain and to identify those belonging also to the Industry 4.0 paradigm. The study confirmed the relationship between Industry 4.0 and Precision Agriculture domains and allowed to create a list of over 1000 technologies referring to the Precision Agriculture domain. This analysis shows how the intersection between the technologies belonging to Industry 4.0 and Precision Agriculture is very broad and makes the two concepts very close from a technological point of view. The dictionary of Precision Agricultural Technologies includes 324 terms. Thanks to a graph, depicted in Figure 1.2, the most cited technologies and the connections between them allowed to identify at least 6 technology clusters (Trivelli et al., 2019).

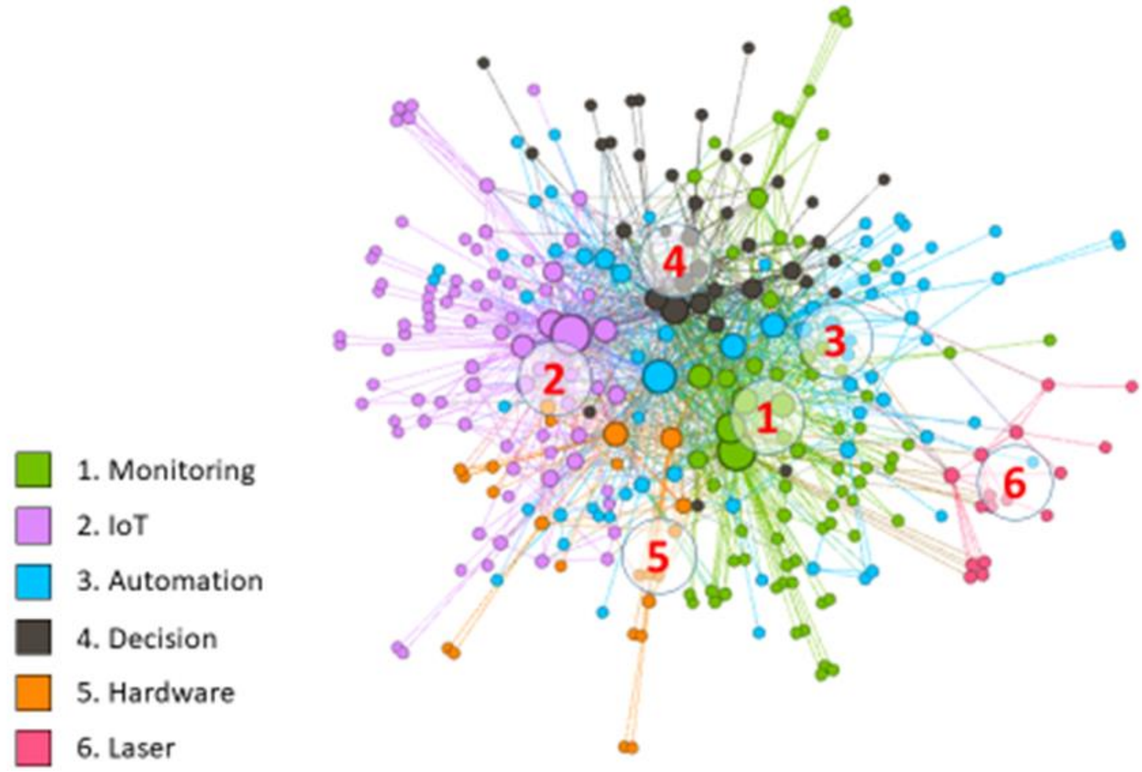

Figure 1.2. Graphical representation of Precision Agriculture dictionary. Source: Trivelli et al., 2019.

The graph in Figure 1.2 shows the structure of the dictionary and the relationships between the technologies that make it up. This representation allows to intensify the connections between the different clusters and technologies. The connections are represented by the lines that join the different nodes (which represent Precision Agriculture technologies) of the graph. The size of the nodes varies proportionally to the number of papers they are mentioned in, instead their position depends on the number of connections between the different technologies: the most connected ones acquire a more central position into the graph and vice versa.

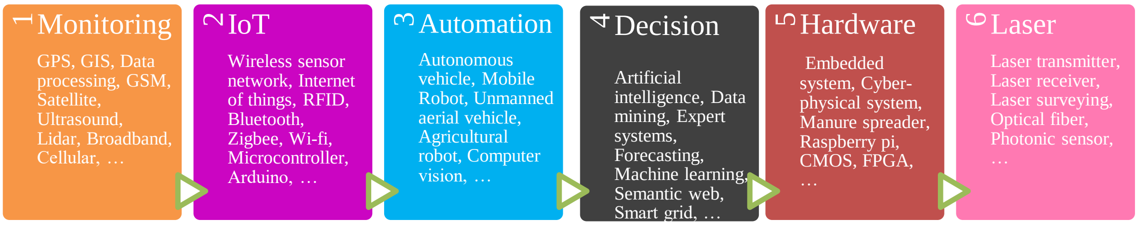

Figure 1.3. Clusters in the Precision Agriculture dictionary

Although it is difficult to classify the applications of Precision Agriculture into such marked categories, which is by its nature an integrated approach of various technologies, this section will describe the various categorizations that emerged from the analysis, as reported in Figure 1.3.

4.1 Monitoring

Monitoring systems represent a key topic in the panorama of studies focused on innovation in the agri-food sector. Since the first launch of terrestrial satellites, monitoring has been one of the priorities in the activity of Earth Observation (EO) (Anuta and MacDonald, 1971; Horton and Heilman, 1973). However, due to image costs and the limited repetition rate leading to the loss of some key stages of crop growth, the potential for EO at the time was very limited (Hunt et al, 2019). The standard terminology for satellite navigation systems is Global Navigation Satellite Systems (GNSS). These systems provide autonomous geospatial positioning with global coverage through the use of satellites. Any GNSS is used to locate the geographic position of a user's receiver anywhere in the world. The availability of these satellites is a fundamental requirement for determining one's position and, in agriculture as in other fields, four main constellations of satellites are now being used to know positions precisely. They are the following:

- GPS (Global Positioning System) or Navstar-GPS, first satellite positioning system used for civilian purposes, it was developed in 1973 by the United States Department of Defense;
- GLONASS (GLObal NAvigation Satellite System), Russian positioning system developed since 1980;
- Galileo, European program started in 2003, not yet fully active;
- BeiDou Navigation Satellite System: a system designed by the Chinese government, active since the beginning of the century and usable only in the Indo-Chinese area.

Currently, there are two operational GNSS systems (GPS and GLONASS) and two others under development (Galileo and BeiDou), which aim to create a wider coverage: from a regional to a global one. The first step in the application of precision farming techniques passes from the application of management choices based on a careful analysis of the variability of soil and crop properties. Land monitoring is an important task in agriculture with applications ranging from food safety control to area and yield forecasting, crop estimation and export planning (Nguyen et al., 2020). Knowing the location during a field operation or establishing a data collection point is essential for the implementation of Precision Agriculture. At the same time, in view of the intended use of the collected information, the points and accuracy requirements of the location may change. The challenges of remote sensing in general and satellite imagery are various, and they have often been found to suffer from some adverse conditions such as solar radiation (Gupta et al., 2019), have inaccurate spatial resolutions and have a low sampling rate, which is an obstacle for applications that work 24 hours a day. Moreover, the spectral indices existing to identify the vegetation areas on satellite images are of an empirical nature; therefore, they require additional specific domain calibration and validation steps when applied to different geographic locations (Nguyen et al., 2020). Satellite images are used in many contexts such as when monitoring desertification (shrubs and grasslands) where it appears to have an accuracy rate between 66% and 79% (McGwire et al., 2000). However, up till now, part of Precision Agriculture monitoring has not been explored (Murugan et al., 2017) even though with the increase and advancement of technology, satellite images are becoming more and more available as far as at time, spatial and spectral scales are concerned. Various image surveys have been proposed to show the difference between cultivated and non-cultivated areas, due to the multispectral nature of satellite images (Huete et al., 2002). New economic and timely remote sensing technologies have been developed to produce maps using satellite images for sustainable solutions. To date, many sources of satellite images are free and integrated with different technologies. They can offer a broad spatial range over the entire globe and therefore, large time spans can be covered. One of the main applications of satellite imagery is agriculture monitoring such as crop variability, crop stages, change detection, etc., where the classification of various crops with soil is done on different resolutions and multi datasets time trend and area estimation are still challenging tasks that require more attention. Techniques for Precision Agriculture monitoring are increasing due to the request for an effective crop supervision which is needed in order to reach an efficient evaluation of crop yield variability. Among the optical satellite systems of interest for Precision Agriculture we can mention Sentinel-2 SPOT (Kussul et al., 2017), Pléiades, RapidEye (Metternicht et al., 2005), Formosat-2, GeoEye-1 and WorldView-1 (Chang et al., 2010).

4.2 Internet of Things (IoT)

The term Internet of Things (IoT) refers to a new technological paradigm in which many objects or "things", such as wireless sensors network, microcontroller and other tools, interact with each other in order to elicit information that help companies to undertake innovation paths (Farooq et al., 2015; Lee and Lee, 2015). Furthermore, as the term "Internet" implies, networking capability is the other core features of the IoT devices (Tzounis et al., 2017). These technologies offer significant opportunities that can contribute to the innovation of many industrial sectors, acquiring an ever-greater centrality in business dynamics (Vermesan and Friess, 2015; Xu et al., 2014). Several factors, including the architecture and technology of the IoT communication network, offer an unprecedented ability to collect and manage a large amount of data by leveraging the application protocols used between nodes, gateways and application servers. The exponential increase in the adoption of the technologies for the Internet of Things has also reached the agri-food sector, increasing the interest in research and innovation towards the development of reliable, verifiable and transparent traceability systems and as Caro et al., (2018) argues, IoT technologies could contribute to food security and the reduction of agricultural and food waste. In recent studies it has been shown that IoT have had a great response in agricultural application (Muangprathub et al.; 2019, Ojha et al., 2015; Talavera et al., 2017; Tzounis et al., 2017). In particular, the agro-industrial and environmental sectors apply the IoT in both diagnostics and control technologies thus contributing to a significant food security and to the reduction of agricultural and food waste (Brewster et al., 2017). According to Talavera et al. (2017), one of its greatest advantages would be the correct tracking of the food, from its origins to the final consumer. Among others it can be mentioned the general use to increase the yield and quality of crops as well as to reduce cultivation costs (Jawad et al., 2017; Rajeswari et al., 2018). Furthermore, through the use of IoT sensors we can reach a constant level of monitoring useful to keep plants at their optimal level of growth. In this way, bad events can be predicted and dealt with in time (Khattab et al., 2019). Smart irrigation systems, developed to replace traditional irrigation, use IoT-based practices and sensor technology as solutions to the lack of resources and water savings required for many types of plants. Furthermore, achieving an optimal use of resources water in agriculture, through the creation of flexible and automated platforms able to cope with soilless needs, is a central issue for the new challenges that Precision Agriculture proposes. IoT technologies through the cloud and edge computing can be an answer to this matter (Huong et al., 2018; Torky and Hassanein, 2020). Another major application of IoT technologies in agriculture occurs in production within greenhouses. In this case, information on humidity, soil, temperature is often collected in real time and subsequently sent to servers for analysis (Zhao et al., 2010). IoT technologies supporting this sector include sensors, RFID, actuators, drones, navigation systems, cloud-based data services and analysis. They offer a variety of decision support tools (Al-Fuqaha et al., 2015; Gubbi et al., 2013; Kumari et al., 2015; Tzounis et al., 2017). Tzounis et al., (2017) argues that sensors and the use of IoT play a central role in the use of Precision Agriculture techniques. In particular, sensors are used by farmers in the field to measure environmental parameters such as temperature and humidity. These data can be used to make production more efficient (Sethi and Sarangi, 2017). Within IoT technologies, a central role is played by Wireless Sensor Networks (WSNs), since almost all IoT applications use wireless data transmission. WSNs are defined, following Akyildiz et al., (2002), as a network of battery-powered sensors interconnected via wireless media and are typically deployed to serve a specific application purpose. The installation of a wireless sensor network, with a view to using Precision Agriculture as an optimization of agriculture, appears to be central for several purposes such as:

- improving the effectiveness and efficiency of farmers intervention;
- helping the farmers make better and well-informed decisions (Capello et al., 2016; Fang et al., 2014; Ojha et al., 2015; Ruiz-Garcia et al., 2009), such as i.e. the air humidity, temperature and transport conditions of the product (Pang et al., 2015);
- helping the farmers to recognize the best time for organizing the harvest, detect plant diseases or estimate fertilizer requirements (López Riquelme et al., 2009).

Following Gubbi et al. (2013) it is possible to obtain better results in terms of IoT vision by applying improvements to the convergence requirements of the WSN. The use of IoT technologies inevitably leads to the accumulation of large amounts of data (called Big Data) which can be useful sources of information for both farmers, technicians and researchers. For this reason, several scholars have focused their attention on the possible uses of these large amounts of data such as i.e. Tzounis et al., (2017) who argued that the management and analysis of these data can be used for the automation of processes aimed at developing forecasting systems with the aim of correcting any errors or activities even in real time. A new cloud computing-based online monitoring model was theorized by Xian (2017). The theory demonstrates that, by integrating different techniques such as Internet of Things, online monitoring system based on cloud computing and following the acquisition of large amounts of data from an IoT system, it is possible to reach a notable analysis of big data in agriculture. New frontier studies also analyze the possible connections between the development of IoT agriculture technologies and the storage of the resulting data. The archived data must be tamper-proof and can be entered by different actors operating along the supply chain in a single database. Several scholars have identified the use of a Blockchain chain (Fernáez-Caramés and Fraga-Lamas, 2018; Tripoli and Schmidhuber, 2018), a sort of peer-to-peer digital book that does not rely on centralized servers and does not allow tampering with third party data, as a solution to this problem. Following the approach of Caro et al. (2018), a new technology called AgriBlockIoT has been proposed. AgriBlockIoT is a completely decentralized traceability system for the management of the agri-food chain aimed at integrating modern Blockchain technologies with information stored with the use of the IoT. Torky and Hassanein (2020) instead propose 5 macro areas of fundamental applications where the Blockchain could be applied with beneficial effects to IoT technologies with the aim of introducing new contributions and improving many functions such as monitoring and traceability, transparency and efficiency at levels of farmers and consumers: farm overseeing, supply chain, land registration, food safety and real time remittance for small farms. Another perspective in studying the possibilities associated with the use of IoT technologies in agriculture is the application of Machine Learning. One of the earliest and best-known definitions of Machine Learning is "the field of study that gives the computer the ability to learn without being explicitly programmed" (Samuel, 1959). Up till now, most of the studies with satisfactory results seem to be aimed at the implementation of machine learning in agriculture: a Support Vector Machine (SVM) (Juhi Reshma and Pillai, 2018) but is also possible to find other applications such as soil management, yield prediction and environmental variables (More and Singla, 2019).

4.3 Automation

The automated management of farms represents one of the most fascinating challenges in the panorama of current Industry 4.0 technologies applied to Precision Agriculture. Agriculture has changed a lot since the last century, moving from a labour-intensive industry into an industry with a power-intensive production system (Sistler, 1987). The digitalization process of agricultural activity, a process that has led to an ever-greater standardization of tasks within the agricultural production process, begun several years ago (Marinoudi et al., 2019). The first signs of the implementation of automation in the agricultural field can be dated back to the early 1980s, when with the development of microcomputers, they were applied to tractors to analyze their performance (Tompkins and Wilhelm, 1982). Through the development of industrial protocols such as the one on agricultural machinery SAE J1939 and the introduction of the ISO 11783 (or ISOBUS) standard, it was possible to set up complete monitoring systems for machinery performance that allow the acquisition of information on the status of the tractor and on the working processes and contribute to the optimization of the overall productivity of the field (Li et al., 2010). Taking as reference the variables of the agricultural sector such as i.e. unexpected rain, a violent hail or sudden heat or cold wave, it can be said that conventional farming practices are not always effective or well-timed in solving some of these problems. The introduction of automation technologies i.e. technologies that, even by exploiting the data resulting from IoT, are able to act autonomously and help to understand the changes in the weather in a timely manner. Automation technologies have been applied in different fields of agricultural techniques. One of these is the soilless cultivation, where thanks to the humidity and temperature control it is possible to have a constant monitoring of the growth process. Other fields of application can be the moment of agricultural harvesting which continuously improves its efficiency or the monitoring of irrigation which can vary water consumption according to the specific characteristics of the soil at the time of irrigation. So, automation is a high-potential technology to improve agricultural productivity. It also supports sustainable economic development (Eberhardt and Vollrath, 2018). Agricultural automation, integrated with new robotic technological models, can overcome human constraints and offer new development prospects as far as the work in the field and its productivity is concerned. Problems related to operations carried on under severe or dangerous working conditions as well as physically exhausting works can be easily overcome by implementing these technologies (Marinoudi et al., 2019). These new possibilities through modern agricultural mechanization and automation technologies however, haven't been fully explored so far; many results have been achieved but many others haven't been put into practice yet. Among the achieved results we remember the development of robots that work as farmers, useful for fertilization, weeding and related to fruit crops (Ren and Martynenko, 2018). Another agricultural limitation that robotic technology can help overcome by improving the environmental sustainability of crops is the current dependence on herbicides (Slaughter et al., 2008). Since the agricultural system is extremely variable by its nature and due to the environmental limits indicated above, the work of robotic technology could be of fundamental importance as it would be able to work regardless of weather conditions, regardless of the size of the objects to be handled and, after a specific, it turns out to be able to react in a dynamic way to any environmental characteristic or structure. Another technology included in the principles of automation is that of Unmanned Aerial Vehicles (UAV). An unmanned aerial vehicle, commonly known as a "drone", is an aircraft with no human pilot on board. The flight of UAVs can be controlled autonomously by on-board computers or by the remote control of a pilot on the ground or in another vehicle (Pedersen and Lind, 2017). UAVs are new alternatives to the use of satellites, which have several critical limitations including the lack of images with optimal spatial and spectral resolutions and an unfavorable review time for most crop stress detection applications which cannot be combined with high spatial resolution and fast delivery times. These limitations could easily be overcome through the implementation of remote sensing sensors positioned on UAVs (Berni et al., 2009; Herwitz et al. 2004). Drones have already been used in agriculture: in the extraction of yield data, in crop management, in crop forecasting and environmental protection, in weed detection and management (Boursianis et al., 2020; Herwitz et al., 2004; Zhang and Kovacs, 2012). Among the technologies used in the automation field, the expert and intelligent system based on artificial vision, algorithms are becoming successful drivers in the management of agricultural business processes. Automation technology based on computerized vision, on the other hand, is being used to increase productivity and efficiency (Foglia and Reina, 2006). The rapid evolution of artificial intelligence has provided many suggestions to improve the efficiency of agricultural production in automation and a more correct and effective management of resources (Vázquez-Arellano et al., 2016). Machine vision technology provides numerous tips and insights to support agricultural decisions and practices thanks to the evolution of techniques such as GPU (Graphics Processing Unit) and DBN (Deep Belief Networks) (Li, et al., 2019; Mochida et al., 2019).

4.4 Decision

Among the technologies supporting decision-making processes in the agri-food sector, the importance of Decision Support Systems (DSS) must be underlined. The DSS concept emerged in literature around the 1970s, when computer-based software was studied for the first time in order to solve problems by analyzing semi-structured and unstructured data (Anthony, 1965; Gorry and Scott Morton, 1971; Simon, 1960; 1965). In the following years, due to their flexible nature, the DSS have made significant contributions to face today's challenges, to make agriculture more productive and sustainable at the same time (Mysiak et al., 2005). Following the approach of Alenljung (2008), a DSS can be defined as an ICT (Information and Communication Technologies) system to support one or more decision makers in making difficult decisions regarding problems not fully structured or semi-structured. The support to the decision maker offered by a DSS system is realized with regard to an ongoing situation or it can involve the decision maker through a decision-making phase to achieve long-term results. Alenjung, (2008) also introduces the concept of ADSS (Agricultural Decision Support System) by classifying it as a mechanism that supports both ongoing activities and future decisions. Hence, the Agriculture Decision Support System is defined as an integrated approach system between man and computer which, using different types of data, can provide farmers with a series of advices to support their decision-making process in various circumstances, therefore, not providing direct instructions or commands to other machinery but management advices to farmers (Zhai et al., 2020). The subdivision of DSS processes theorized by French et al., (2009) is interesting. Starting from a breakdown of the categories based on the domain of activity and the level of decision support, they are divided as follows (Figure 1.4):

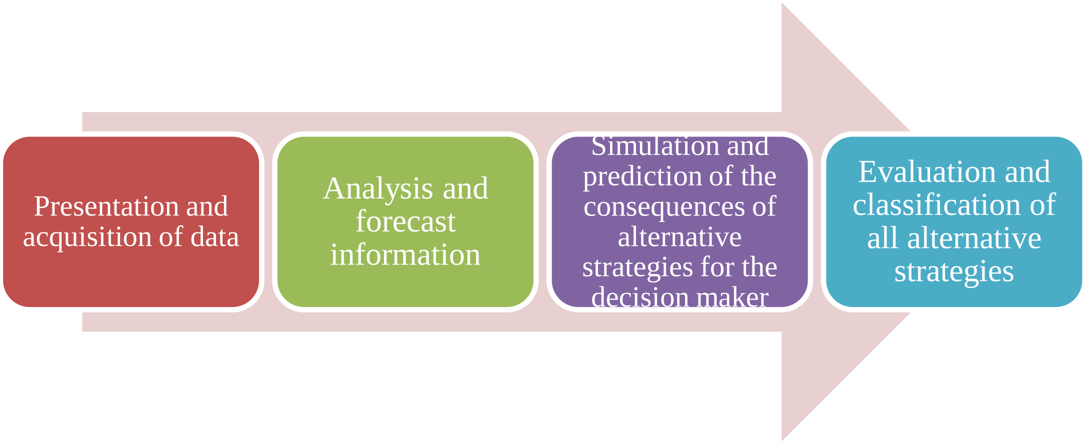

Figure 1.4. DSS processes theory. Source: elaboration on French et al., 2009

Furthermore, DSS can be broken down into five components: basic models, database, knowledge, graphical interfaces (Mansouri et al., 2012; Turban et al., 2005) and end user (Marakas, 2003; Taechatanasat and Armstrong, 2014). In literature, several authors support the effectiveness of these tools; it is useful to remember the application of DSS in the analysis of food safety and quality (Wijtzes et. al, 1998), on the compaction of agricultural soils (Canillas and Salokhe, 2002), when dealing with the reduction of waste in wine production (Musee, et. al, 2007). Furthermore, it is a support for logistic managers in identifying the most effective solution to implement in their activities. Other fields of application of DSS in agriculture can be found in the different moments of cultivation management such as the phase of wheat growth using the color processing of the cultivation images (Kakran and Mahajan, 2012), integration with the use of NDVI sensors (Lopes and Reynolds, 2012; Tamayo et al. 2010) or with the creation of integrated models, useful in various phases such as i.e. CropSyst (Stöckle et al., 2003), APSIM model (Keating et al., 2003) or AgroDSS (Rupnik, et al., 2019). Other studies show its application to different types of crops, such as rice or pomegranates or to predict pest incidence (Adinarayana et al., 2012; Patil et al., 2012). Furthermore, through the DSS tool, solutions can be implemented in the agricultural context aimed to optimize processes which may include the identification of a correct timing for the sowing phase and a better use of water resources that can be framed in the paradigm of environmental and economic sustainability (Trogo et al., 2015). The use of DSS during irrigation can in fact help the farmer to improve the profitability of the fields through a proper management. Obviously, the solution in irrigation management is up to the farmers: it is considered the simplest application as it can work with minimal input data and therefore there is no need for professional advices (Bonfante et al., 2019). Although DSS technologies have offered, over the years, effective outputs through intuitive interfaces based on the use of computers, mobile technologies used in the "decision-making process" are also to be mentioned (Antonopoulou et al., 2010). Although it seems clear that the DSS could play a central role in agriculture as tools of support and help to the farmer, their implementation has not reached their maximum expressible potential. The implementation process is particularly complex due to the nature of the interrelationships between the various levels of the production system, the interactions between decision levels, the diversity of farms and farmers in a given area and the impacts given by stochastic events (Le Gal et al., 2011). The reasons of the difficulty to overcome these problems seem to be different, among which we can include a limited attention in current research (Aubert et al. 2012; Le Gal et al., 2011), a not yet global approach in the management of the field due to high complexity of the decision-making process of farmers called "the implementation problem" (Eastwood et al. 2012; Lundstrom et al., 2015; Matthews et al. 2008; Rossi et al. al. 2014). Even its spread among farmers and its adoption rate remains at low or, in some cases, marginal levels compared to other Precision

Agriculture technologies. A motivation of the matter is given by Lindblom et al., (2017), who states that researchers and scientists are unable to understand the tacit knowledge and practical needs of farmers while farmers perceive these systems as too complex and difficult to deal with. Thus, according to Lindblom et al. (2017), one of the main solutions for the "implementation problem" could be a set of laws capable of developing the new technology without considering the actual needs of end users (Lundstrom et al., 2015).

4.5 Hardware

WSAN technologies (Wireless Sensors and Actuators Networks) in agriculture, as in other sectors, appear to be in a moment of great pervasiveness. One of the reasons behind this expansion is the new approaches and improvements in the hardware systems, after going further the problems of design and standardization of outdated protocols (Gaura et al., 2010; Piromalis and Arvanitis, 2016). A recent study, carried on by the University of Hokkaido in Japan, has categorized all the hardware changes that have occurred from 1990 to 2018 as far as Autonomous Vehicles (AV) used in agriculture are concerned. The main categories identified in changes were: procedure, the type of platform used, the transportation type, the AV's functionality in operation, the communication type and the sensors used (Roshanianfard et al., 2020). Much of the work regarding the improvement of hardware components comes from the implementation of Open-Source Hardware (OSH), hardware that can be exploited by anyone without paying fees. The exploitation of these technologies, which are very sensitive to the question of the cost-effectiveness and of the implementation of the technology, are of great expansion in developing countries, especially as regards greenhouse agriculture (Babu, 2013). The development of OSH is intended for commercial markets and therefore it may have the stability, robustness and accuracy for other applications as well (Mesas-Carrascosa et al., 2015).

Hardware Platforms for IoT

The major hardware applications in the field of technological integrations in agriculture concern the IoT hardware platforms, made up by different components able to run the required software to let machines work. As part of a software committed to agricultural crops, it is therefore necessary to develop a system of hardware that can make them work and integrate with other technologies as Precision Agriculture suggests. Several hardware have been developed so far among which is possible to remember the Raspberry PI, Arduino, NodeMCU and Beaglebone. Raspberry are a series of single-board computers, operating as real computer systems and with multitasking functionality, developed in the United Kingdom by the Raspberry foundation. In fact, Raspberry hardware can be used for many functions, including the management of the application of fertilizer to the soil (Flores et al., 2017), the monitoring of insects with the aim of pest control (Zhong et al., 2018), the Smart drip irrigation and general soil monitoring with relatively low costs (Mondal et al., 2017; Su et al., 2016). The Arduino hardware, of Italian production since 2005 at the Interaction Design Institute of Ivrea, is a microcontroller positioned above a printed circuit equipped with sockets to allow a connection to external devices with digital and analog inputs and outputs (Koenka et al., 2014; Mesas-Carrascosa et al., 2015). Used mostly in irrigation management, it offers various solutions (Arvindan and Keerthika, 2016; Salvi et al., 2017; Shekhar et al., 2017) and it is also applied to hydroponics (Crisnapati et al., 2017; Sihombing et al., 2018) as well as in offering various soil monitoring solutions while maintaining the economy of the technological plant (Math and Dharwadkar, 2017). NodeMCU is, on the other hand, an open-source platform developed for integration with the IoT. Developed in 2014 it generally refers to firmware rather than the development kits (Kour and Arora, 2020). Used in highly integrated systems it sees its application mostly in water system controls and irrigation technologies for agricultural crops (Parthasarathy et al., 2019; Premkumar et al., 2018). More recent studies see the use of the Node MCU in the construction of low-cost weather stations

(Singh et al., 2020). Beaglebone is a low-cost computer community supported development platform for developers. This hardware sees its application in data collection to support the correct use of pesticides by integrating it with artificial neural networks (Faiçal et al., 2016) or tool to identify the physic-chemical properties of the soil as apparent Electrical Conductivity (ECa) sensors (Queiroz et al., 2017). It is often referred to as an easily integrated and low-cost technology (Coelho et al., 2020; Queiroz et al., 2020). The use of hardware in agriculture is however various and may have different applications. The advantages are mostly related, in the case of OSHs, to the low purchase and implementation costs for companies as well as to the high level of customization problem solving. In fact, starting from basic situations, they can be easily modified and applicable to different types of crops. The greatest potential of applications are precisely the developing countries where it will be possible to improve production in terms of crop volumes and quality and have a constant environmental management monitoring at low cost (Mesas-Carrascosa et al., 2015).

4.6 Laser

With the progress of technological frameworks, laser sensors are assuming an increasingly central role in modern agriculture, in fact, laser-controlled ground leveling has been adopted in Europe, the United States and other developed countries for over 30 years (Zheng et al., 2007). With a view to an integrated application of different technologies, where the exchange of information is instantaneous and wireless, lasers seem to be the ideal technology to respond to a series of needs. Although the use of lasers has been widely cleared also in the agricultural field, this field of application usually comes, after its implementation, in the medical field while laser speckle is being used in agriculture. This new low-cost, sensitive and non-invasive technology turns out to be interesting for many applications, being a vehicle for the possibility of making a fast and non-destructive sampling and providing new parameters, such as dispersion or absorption of supports and which can be of great help in agricultural techniques (Ryckewaert et al., 2020). For vehicle-based determination of crop biomass, commercially available laser scanners have been analyzed and tested to measure aboveground biomass in oilseed rape, winter rye, winter wheat, oats and grassland (Ehlert et al., 2010). Laser scanners are also used for crop height detection. The leveling of the ground controlled by the laser appears to be very precise and efficient, especially when compared to traditional agriculture techniques that involved the use of animals or tractor blades. Research shows that an effective application of these technologies is found in soil leveling processes, with improvements in crop activities as far as an increase of the efficiency and precision of the processes and the yield and the quality of the products are concerned. (Li et al., 1999; Zheng et al., 2007). Among the recently applied techniques, the Laser Induced Breakdown Spectroscopy (LIBS) has to be mentioned. The LIBS system is a spectroscopic analytical technique that requires little or no sample preparation and following an appropriate calibration can evaluate a sample in seconds and quantify its elemental concentrations (Villas-Boas et al., 2020). The applications of this new LIBS technology appear to be varied in agriculture, such as most of the generic analyzes for soil and plants and also new applications on finished products to evaluate nutritional elements and food supplements (Peng et al., 2016).

5. The survey: objective and method

The general objective of the present research is to investigate the knowledge of the Italian farmer about the above-mentioned technologies, the perception of utility, the use and the willingness to invest in technology. Specifically, through 4 precise questions addressed to farmers regarding knowledge of individual technologies, perception of their usefulness, rate of use and willingness to invest in technological categories, the objective is to promote technological spreading by bridging the existing gap between the individual technological innovations available on the market and the actual knowledge and subsequent adoption by farmers. In this regard, an online survey was carried out, using the Snowball sampling method, among the largest number of reachable farmers and involving the main Italian trade associations (Confagricoltura, Coldiretti, Confederazione Italiana Agricoltori). For the drafting of the questionnaire, a survey based on mostly closed questions was developed. Questionnaire setup followed general scientific standards for online questionnaires as suggested by Baruch and Holtom (2008), Cook et al., (2000), Couper (2000), Couper et al. (2001), Hooker and Zuniga (2017). Snowball sampling was chosen, considering the large number of Italian farmers and their reluctance to release information. In this respect, Snowball Sampling appears to be the most effective method to get the maximum number of answers and increase the spreading of the survey (Goodman, 1961; Sadler et al., 2010; Wayman et al., 2019).

6. Data and results

The data were provided by an empirical study of Italian farmers that collected information on general data such as:

- Knowledge and adoption of the PA technologies in Italy;
- perception of utility of the PA technologies;
- willingness to invest in PA technologies.

The data were collected from the end of July 2020 to the beginning of November of the same year. The online questionnaire was spread through the Google Form platform; its link was initially sent to the regional and provincial sections of the main Italian farmers associations and subsequently distributed via social networks (Facebook groups specifically committed to agriculture) and then directly to farmers. Before being submitted, the questionnaire was checked and tested by a team of experts including Professors of Economics, a PhD student from the Department of Agriculture and several farmers from the "Piana del Sele" an important area in Salerno. Overall, data from 755 farmers were collected through the questionnaire and used in the analysis. The questionnaire was built in blocks with key questions, in any case the respondents had access to 2 minimum blocks of questions. The respondents were then aggregated into macro categories of farmers, structured as follows:

- Uninformed farmers: Farmers who were unfamiliar with Precision Agriculture (Do you know Precision Agriculture? No, I don't)
- Informed Farmers: Farmers who were aware of Precision Agriculture (Do you know Precision Agriculture? Yes, I do)
- Informed and Adopters Farmers: Farmers who knew and used PA: (Have you ever adopted PA techniques in your company? Yes, I have)
- Informed and Non-Adopters Farmers: Farmers who knew about PA but didn't use it: (Have you adopted PA techniques in your company so far? No. I haven't)
- Farmers willing to invest in PA in the next three years (Do you intend to invest in Precision Agriculture in your company in the next three years? Yes. I do)

Although the total interviewees are 755, the different groups have different distribution. Uninformed farmers, i.e. those who are unfamiliar with precision agriculture, are 389, while those who claim to know it are 366. Of the latter, those who use at least one of the techniques in their companies are 154, and of these, 135 declare they want to expand its use in the next three years. On the other hand, those who have knowledge of Precision Agriculture techniques but do not use any of them are 211. Of these, however, 145 are ready to invest in the adoption of Precision Agriculture techniques in the next three years.

Informed Farmers: Farmers who say they know Precision Agriculture (Do you know Precision Agriculture? Yes, I do)

As for informed farmers, that are those who when asked "Do you know Precision Agriculture?" answered "Yes" a dedicated block of questions was prepared. The farmers with knowledge of the PA detected by the survey were 366. As shown in Figure 1.5, it is graphically represented which technologies the respondents indicated to the answer "Which of these Precision Agriculture techniques do you know?". For this question more than one answer was allowed. The best-known technologies are those of Monitoring (GPS, GIS, Data processing, GSM, Satellite, Ultrasound, Lidar, Broadband, Cellular) known by as many as 322 farmers. Followed by those of Automation (Autonomous vehicle, Mobile Robot, Unmanned aerial vehicle, Agricultural robot, Computer vision) known by 184 and of IOT (Wireless sensor network, Internet of things, RFID, Bluetooth, Zigbee, Wi-fi, Microcontroller, Arduino) known by 156. Laser (Laser transmitter, Laser receiver, Laser surveying, Optical fiber, Photonic sensor) and Decision (Artificial intelligence, Data mining, Expert systems, Forecasting, Machine learning, Semantic web, Smart grid) are known respectively by 124 and 105 farmers. The least known category is Hardware (Embedded system, Cyber-physical system, Manure spreader, Raspberry pi, CMOS, FPGA) with only 72 farmers who declare that they know their applications in PA.

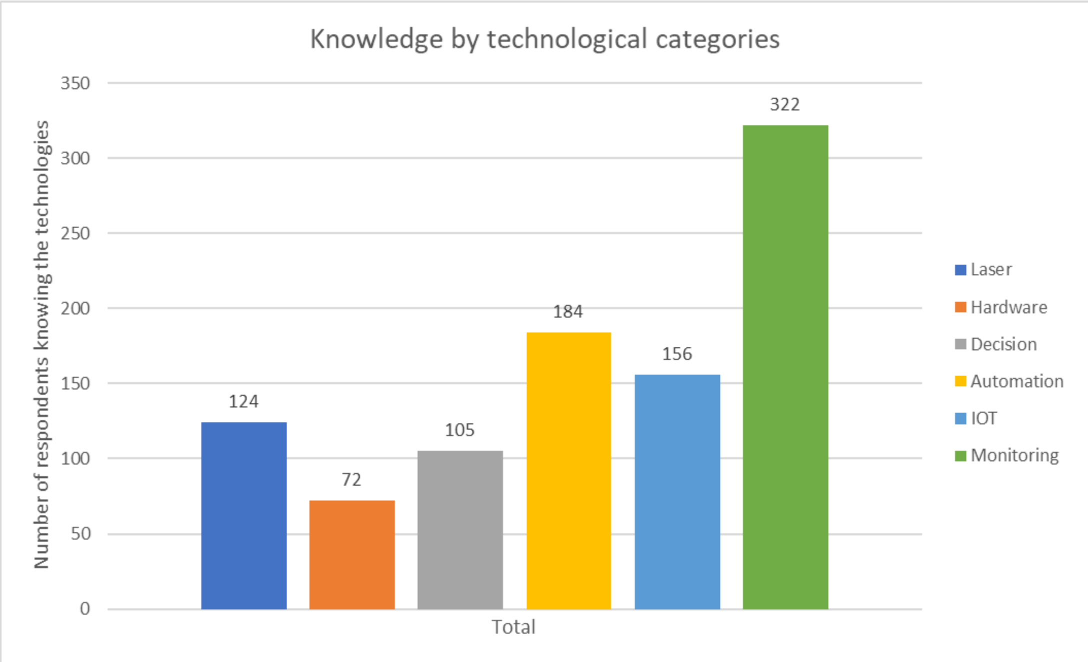

Figure 1.5. Knowledge by technological categories

For the same technologies, farmers were then asked which ones they considered most useful for their activity. Also, in this case more than one answer was allowed. Monitoring category is perceived as more useful with 278 answers followed by Automation with 137, IOT with 132 and Decision with 114. Hardware categories with 57 and Lasers with 49 are less perceived as useful (Figure 1.6).

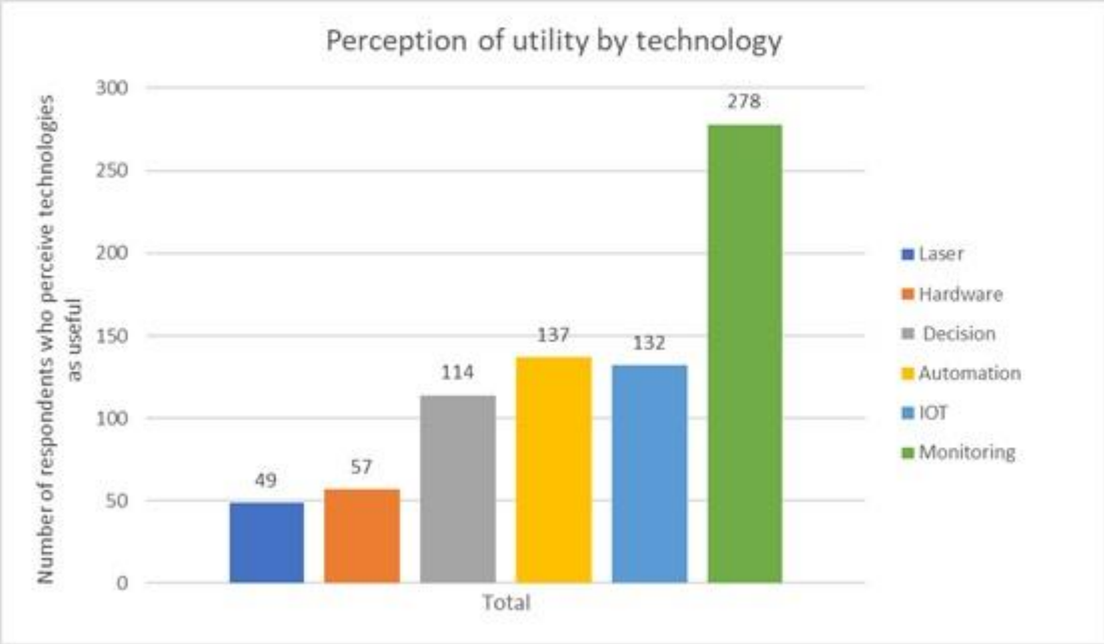

Figure 1.6. Perception of utility by technology

The adopters were then asked what type of PA technology they used, as shown in Figure 1.7. For this question more than one answer was allowed. The most widespread technologies are the Monitoring ones, used by 137 farmers. Follow those of IOT used by 84 and those of Automation and Decision for both categories are 69 farmers who declare their use. 63 farmers claim to use technologies related to the use of lasers and 60 to implement the use of hardware in agriculture.

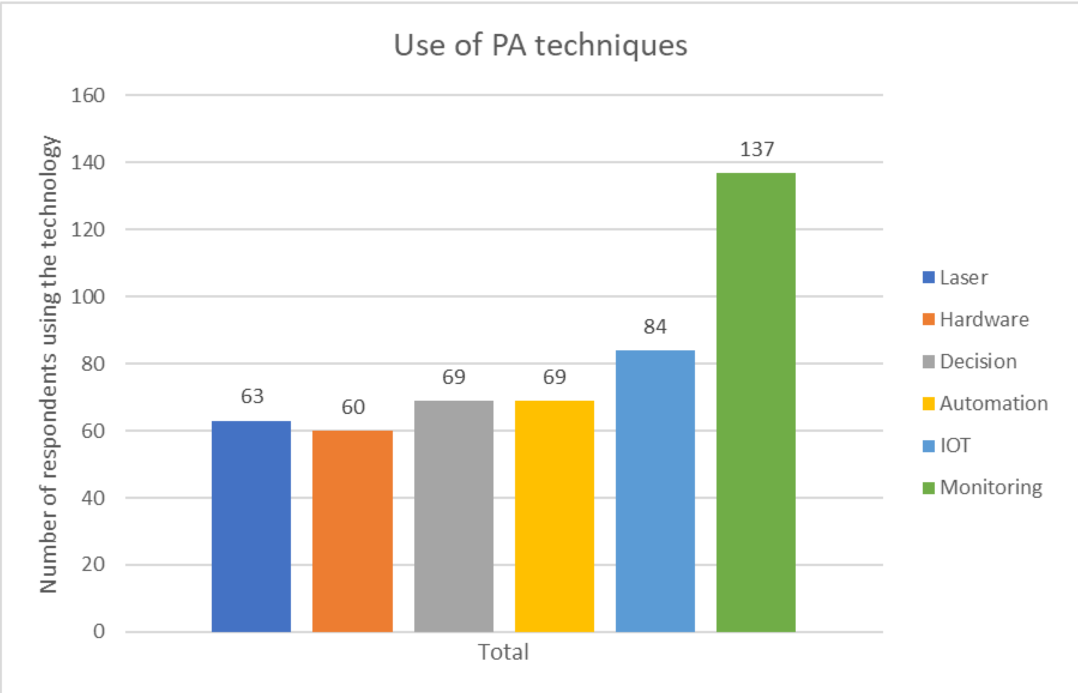

Figure 1.7. Use of PA techniques

As for farmers who want to invest in PA in the next 3 years, regardless of whether they are already users or not (N=280), it was initially asked in which technological sectors they would like to invest. For this question more than one answer was allowed. Monitoring is always in first place, with 165 responses that are worth the will to invest in this technological sector. Automation follows, where they declare they want to invest 124 farmers and IOT where they would like to invest in 104. 77 farmers declare they want to invest in Decision technologies, 41 in Hardware and 35 in Lasers (Figure 1.8).

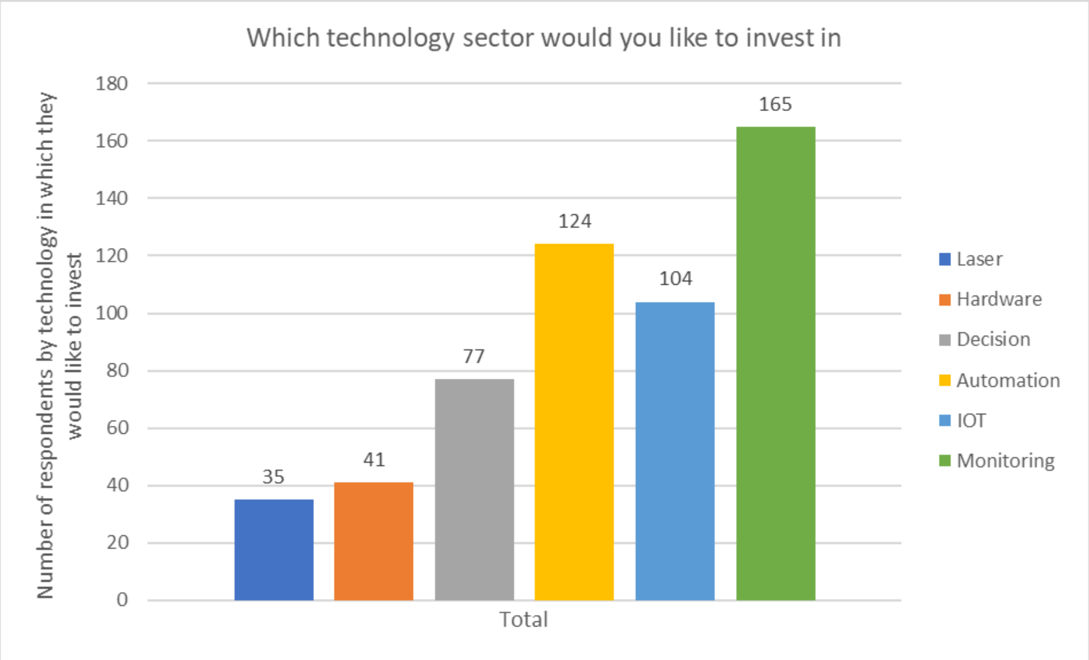

Figure 1.8. Which technology sector would you like to invest in

7. Discussion

The present research has set the aim of detecting the rate of knowledge of the technologies used in agriculture, classified by macro-area following the approach given by Trivelli et al. (2019). It is possible to detect the peculiarity of the Italian agricultural context which, highly diversified internally, presents structural differences with respect to its European counterparts and the rest of the world. The agricultural sector is in fact characterized by a strong fragmentation being made up of a multitude of small and very small companies in size and, although the trend in recent years has been reversing with the aggregation of various companies and the consequent growth in terms of average hectares per single company, this factor could be an impediment to the knowledge and subsequent adoption of the various types of technology. In fact, precision agriculture sets itself the goal of integrating different types of technologies, making adoption even more difficult for a sector that is still made up of many small companies. Individual farmers were asked, via an online survey, which technologies they knew, which ones they found most useful for their company, which ones they adopted and which technologies they would like to adopt in the three years following the analysis. Monitoring technologies appear to be both the best known and those perceived as most useful, followed by those of the IOT and Automation. Decision-making technologies, such as DSS, are not widely known or used but are often perceived as useful, reflecting the great curiosity of farmers towards this sector. As far as the willingness to invest is concerned, also in this case farmers show greater intention towards Monitoring and Automation technologies, followed by those of IOT.

8. Conclusion

To date, the evolution of digital techniques in the framing logic of innovation technology inherent in the Industry 4.0 paradigm has made many steps forward. The growing diffusion of digital technology techniques in a context of Precision Agriculture aimed at marginalizing the costs and the pervasiveness of the Industry 4.0 paradigm in the agricultural context may favor innovative processes in the primary sector and face new challenges deriving from the current socio-economical context. The agricultural sector and investors seem to have welcomed the PA market with great interest, although the margins for improvement still seem to be great in order to exploit its full potential. However, many efforts still need to be made. This study aims to be a starting point for understanding which technologies are most widespread among Italian farmers and which ones are perceived as most useful with the aim of increasing diffusion through models of technological integration. The new technological paths also deriving from the integration of the six technologies clusters identified from the Industry 4.0 paradigm also find great correspondence within the digitization path of the agricultural sector. Although the agricultural composition of Italian companies presents a strong fragmentation and a composition formed mostly of small and medium-sized enterprises, which are more affected by difficulties in the technological adoption process (Elijah et al., 2018), the path taken seems to be the correct one with a growth in terms of knowledge of new technologies and technological adoption there still seems to be great room for improvement, improving communication between farmers to increase their level of knowledge of individual technologies, passing through the adoption and knowledge of the possibilities deriving from technological integration.

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