La borsa di dottorato è stata cofinanziata con risorse del
Programma Operativo Nazionale Ricerca e Innovazione 2014-2020 (CCI 2014IT6M2OP005),
Fondo Sociale Europeo, Azione I.1 “Dottorati Innovativi con caratterizzazione Industriale”

UNIONE EUROPEA
Fondo Sociale Europeo

Ministero dell'Istruzione,
dell'Università e della Ricerca

PON
RICERCA
E INNOVAZIONE
2014 - 2020

UNIVERSITÀ DEGLI STUDI DI FOGGIA

Dipartimento di Scienze Agrarie, Alimenti, Risorse Naturali e Ingegneria (DAFNE)

Corso di Dottorato di Ricerca in Gestione dell'Innovazione nei Sistemi Agro-Alimentari della Regione Mediterranea
(Ciclo XXXV)

The Adoption of 4.0 Agriculture for Wine Production in Order to Improve Efficiency, Sustainability and Competitiveness

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Abstract

The imperative to feed a global population of approximately 10 billion people within the next 30 years, amid challenges like resource scarcity and environmental concerns, has catalysed the emergence of Agriculture 4.0. This paradigm shift involves integrating emerging technologies such as robotics, artificial intelligence, and the Internet of Things into traditional agri-food systems, and precision agriculture technologies. In the wine industry, deeply rooted in tradition, Agriculture 4.0 presents a promising solution to enhance efficiency, sustainability, and competitiveness. By leveraging data-driven decision-making, automation, and precision agriculture techniques, vineyard management, grape cultivation, and wine production could undergo a fundamental transformation. The thesis explores the multifaceted aspects of Agriculture 4.0 adoption, exploring technologies, strategies, and case studies to assess its impact on efficiency. Additionally, it addresses challenges and barriers hindering the widespread adoption of these technologies.

However, the adoption of precision viticulture, a crucial component of Agriculture 4.0, introduces a differentiated management approach to vineyards. This approach aims to enhance efficiency, quality, and sustainability by utilizing tools such as georeferencing, remote sensing, and wireless sensor networks. Despite the increasing prevalence of Industry 4.0 technologies, a notable research gap exists in understanding their nuanced application within viticulture. Unique challenges, including data compatibility and environmental sustainability, necessitate focused investigation. Therefore, the thesis seeks to fill this gap by examining the distinctive challenges and opportunities associated with the adoption of 4.0 Agriculture in viticulture, providing valuable insights for stakeholders, policymakers, and researchers.

The primary research objectives of the thesis centre around investigating how the adoption of agricultural innovations, particularly precision agriculture, affects the technical efficiency of Italian farm production. The study explores the impact of precision agriculture on input use and technical efficiency, employing a Data Envelopment Analysis (DEA) method. By contributing to the existing literature on technology adoption, the research aims to provide valuable insights for policymakers, investors, and farmers, fostering a more sustainable and prosperous future for the agri-food sector.

The thesis evolves across seven chapters, each contributing to a comprehensive understanding of the adoption of Agriculture 4.0 in vineyards and agricultural produces in general. Each chapter attempts to lay the groundwork for answering the research question. In particular, Chapter 01 introduces the background, the problem, and the research question, while chapter 02 describes the trends of recent innovation in agriculture where agriculture 4.0 and precision viticulture technologies were discussed and reviewed in detail along with their potential applications. Chapter 03 describes the diffusion process of agricultural innovation and different models and theories behind this process. Chapter 04 reviews the literature on the different factors which affect

the adoption of precision agriculture technologies in the context of Italy. In particular, a scoping review is performed to investigate the determinants which can potentially be triggering or hindering farmers to adopt agricultural innovations. Chapter 05 describes the theoretical background related to efficiency analysis empirical work. First, the production function and the key performance indicators to evaluate farm performances, such as productivity and technical efficiency, are introduced. Subsequently, methods used to evaluate technical efficiency are reviewed. Chapter 06 first presents the methodology implemented in this thesis, based on a model developed in the recent literature. In particular, it describes the Data envelopment approach and Ordinary least squares (OLS) regression. Then, the descriptive statistics of the Farm Accountancy Data Network sample are reported, as well as the results of the estimated model. Ultimately, the findings of this analysis are discussed, providing some conclusions. Finally, Chapter 7 discusses the results, summarizes the main conclusion of the thesis, and highlights the limitations and future research directions.

Chapter 1 General Introduction

1.1 Background

The task of ensuring food supply for a population of around 10 billion individuals during the next 30 years, given the limited availability of natural resources, has led to the investigation of alternate ways of production (Hickey et al., 2019). The objective is to achieve optimal efficiency and economic viability in agriculture while minimizing the negative impact on the environment (Ayaz et al., 2019). The problem has resulted in the development of alternative production systems that utilize emerging technology in different institutional and political settings (Lioutas and Charatsari, 2020; Herrero et al., 2020). Various technological options, such as robotics, artificial intelligence, agricultural internet of things, big data analytics, machine learning, unmanned aerial vehicles, genetic engineering of plants, and vertical agriculture, are being considered as promising solutions in scientific debates (Klerkx and Rose, 2020; Rose et al., 2021; Liu et al., 2020; da Silveira et al., 2021; Wolfert et al., 2017; Raj et al., 2021; Hofmann et al., 2020; Halgamuge et al., 2021). The objective of these technologies is to update traditional agri-food systems and mitigate environmental harm and social disparities (Sumberg and Giller, 2022; O'Malley et al., 2020). These technologies aim to modernize conventional agri-food systems while reducing social inequalities and environmental damage (Lajoie-O'Malley et al., 2020)

Researchers have referred to the development of the modern agri-food system as "agriculture 4.0" or the fourth agricultural revolution. Due to its recent emergence, scholars in the field are now revising the definition of Agriculture 4.0 (Barrett and Rose, 2020). Agriculture 4.0 refers to the incorporation of advanced technologies and creative services in agriculture, which requires a change in culture and behavior among all participants in the agricultural production process. The objective is to optimize productivity, efficiency, and sustainability in agriculture by leveraging accurate, up-to-date data for well-informed strategic decision-making (da Silveira et al., 2021).

Wine production has long been steeped in tradition and artisanal craftsmanship, with vineyards and wineries relying on age-old techniques, passed down through generations. However, in today's rapidly changing world, the wine industry faces an array of challenges, from increasing competition and climate change to resource scarcity and consumer demands for sustainability. To address these pressing issues, a new paradigm has emerged: the adoption of 4.0 agriculture in the wine sector. This shift promises to revolutionize the way wine is produced, offering solutions that enhance efficiency, sustainability, and competitiveness. Agriculture 4.0, also referred to as Smart Farming or Agriculture 4.0, is a concept that originates from the larger framework of Industry 4.0. It includes employing innovative technologies like the Internet of Things, also known as IoT, Artificial Intelligence or (AI), big data analytics, and automation into agricultural practices. In the context of wine production, this entails a fundamental transformation in how vineyards are managed, grapes are cultivated, and wines are made (Oreški et al., 2021).

Efficiency is one of the primary driving forces behind the adoption of 4.0 agriculture in the wine industry. Traditional wine production methods can be labour-intensive and time-consuming, with many processes relying on manual labour and expert intuition. By harnessing the power of data-driven decision-making and automation, vineyard managers can optimize crop yields, reduce resource wastage, and streamline production schedules. This increased efficiency not only lowers production costs but also ensures a consistent and high-quality product, meeting the demands of today's discerning consumers. Sustainability is another critical aspect of modern wine production. As the effects of climate change become increasingly evident, vineyards are at risk from shifting weather patterns, rising temperatures, and extreme weather events. Adopting 4.0 agriculture practices enables vineyard operators to monitor environmental conditions in real time and make data-informed decisions to mitigate risks. Furthermore, precision agriculture techniques help reduce water and pesticide usage, minimizing the industry's impact on the environment and promoting a more sustainable approach to wine production (Oreški et al., 2021)

Competitiveness in the global wine market is essential for vineyards and wineries to thrive. As consumer preferences evolve and market dynamics change, staying ahead of the competition is a constant challenge. 4.0 agriculture provides the tools necessary to adapt to these shifting landscapes. By employing AI-powered predictive analytics, vineyard operators can anticipate market trends, optimize marketing strategies, and tailor their wine offerings to meet consumer demands more effectively. This newfound agility not only helps maintain market share but also opens up opportunities for growth and diversification. Therefore, this thesis will delve into the various facets of 4.0 agriculture adoption within the farms producing vineyards and also other crops, exploring the technologies, strategies, and case studies that exemplify its potential. This will examine the impact of 4.0 agriculture on efficiency, providing insights into how vineyards can leverage these advancements to enhance their operations. Furthermore, this study will consider the challenges and barriers to the adoption, of these challenges.

1.2 Problem statement

Technological innovations have led to the revision of the techniques to improve, and enhance production and sustainability objectives, with a more efficient use of the use of production factors to contain costs and ensure sustainability. Precision viticulture represents a differentiated management approach that aims to meet the real needs of each parcel of the vineyard (Bramley R. et al., 2003; Bramley RG and Williams SK., 2001; Taylor JA., 2004; Proffit T. et al ., 2006). It is based on tools which, using a wide range of observations relating to the spatial variability of the vineyard, provide recommendations for improving management efficiency in terms of quality, production and sustainability. These tools are represented by georeferencing (Vieri M. et al., 2012), by remote sensing (Marçal AR and Cunha M., 2007; Gago J. et al., 2013; Baluja J. et al., 2012), by technologies of the wireless sensor network (WSN) (Ruiz-Garcia et al., 2009; Burrell et al., 2004). The new technologies to support the management of the vineyards and the cellar activities make it possible to improve management efficiency and production quality by reducing the impact on the environment. At present there are few studies relating to the potential benefits deriving from the adoption of precision viticulture (e.g. Bramley et al., 2005; Lescot et al., 2011) and little attention has been paid to the analysis of the economic efficiency of the use of these technologies in a winery. In addition, the potential benefits in terms of reducing vulnerability to climate risks and increasing resilience have not been sufficiently evaluated.

Despite the increasing prevalence of Industry 4.0 technologies across various sectors, there exists a notable gap in research exploring the nuanced application of these technologies within viticulture. The unique challenges of the wine production process, including aspects of data compatibility, sensor technology, and network infrastructure, pose potential barriers to the seamless integration of 4.0 Agriculture. Furthermore, the environmental impact and sustainability implications of these technologies in the context of wine production remain unclear. Therefore, the current thesis investigate and address the distinctive challenges and opportunities associated with the adoption of 4.0 Agriculture. By addressing these challenges, the thesis endeavours to address a holistic understanding of the adoption of 4.0 Agriculture in vineyards, and agricultural produce in general, and contribute valuable insights for industry stakeholders, policymakers, and researchers, thereby guiding the industry towards a more sustainable, efficient, and competitive future.

1.3 Research Objectives

The aim of the present work is to investigate how agricultural innovation adoption affects the technical efficiency of Italian farm production. In particular, the objectives of the current study are to examine the effects of precision agriculture adoption on adoption on the input use, and technical efficiency of Italian agricultural producers.

To analyze the above-mentioned relationships, firstly, the literature that describes the types and core technologies in agricultural innovations and their potential applications in the agricultural context. Then the literature review to briefly highlights the diffusion process of innovative agricultural technologies, and the theories behind them. Subsequently, the scoping review proposed by Tricco et al. (2018) aimed to investigate the factors responsible for technology adoption by Italian farms. Then, the literature explores the methods to analyze technical efficiency in the context of technology. Finally, to estimate the effect of precision agriculture technologies on input use, and technical efficiency, a Data envelopment analysis (DEA) method was implemented.

The contribution of this research refers to the inclusion of precision agriculture adoption in in the data envelopment framework model to investigate the effect of precision agriculture on technical efficiency on input use, and farm performance. More specifically, this thesis seeks to determine if precision agriculture adoption might enhance technical efficiency of farmers. Certainly, there is no simple answer to this question due to the multifaceted nature of the farming system and different types of precision technologies.

To sum up, understanding the impact of precision agricultural technologies on the technical efficiency of farms can assist policymakers, investors, and farmers in promoting the use and adoption of these technologies. This support can contribute to the agri-food sector's shift towards a more sustainable and prosperous future.

The findings of this thesis may guide the policymakers in the design of policies concerning technology adoption which target to increase the results of farms in economics and environmental terms. Moreover, it may convince farmers to increase the adoption of innovative agricultural technologies. Even though the Italian government provides one of the highest subsidies in the world, the incentives for precision agriculture are quite scarce and concentrated in some regions (Enjolras et al., 2012). Finally, this work aims to guide wine enterprises and policymakers in adopting the effect of technology to enhance their production and market competitiveness. One of the main problems related to the diffusion of this technology is the high investments and education required to fully understand the technology. Therefore, this study's purpose of investigating these relationships may provide results to measure the effect of the precision agriculture techniques on technical efficiencies and hence paving the way towards more adoption intensity.

1.4 Thesis Outline

The remainder of the thesis is composed of 07 chapters. Each chapter aspires to build the path to arrive at to reply to the central research question. The second chapter describes the trends of recent innovations in agriculture. Then, the theories and models are mainly employed in the diffusion of agricultural innovations (chapter 03). Afterwards, a scoping review of factors affecting precision agriculture adoption in Italy is briefly highlighted (chapter 04). Then conceptual framework and theoretical background related to the production function, productivity and technical efficiency were illustrated (chapter 05). Finally, the methodological framework which refers to technical efficiency analysis of Italian farms using Data envelopment analysis and the Farm Accountancy Data Network, and model specification implemented to examine the case study of the present work are presented (chapter 06).

Specifically, Chapter 02 describes the trends of recent innovation in agriculture where agriculture 4.0 and precision agriculture technologies (PATs) or precisely precision viticulture technologies were discussed and reviewed in detail along with their potential applications.

Chapter 03 describes the diffusion process of agricultural innovation and different models and theories behind this process.

Chapter 04 reviews the literature on the different factors which affect the adoption of precision agriculture technologies in context of Italy. In particular, a scoping review is performed to investigate the determinants which can potentially be triggering or hindering farmers to adopt agricultural innovations.

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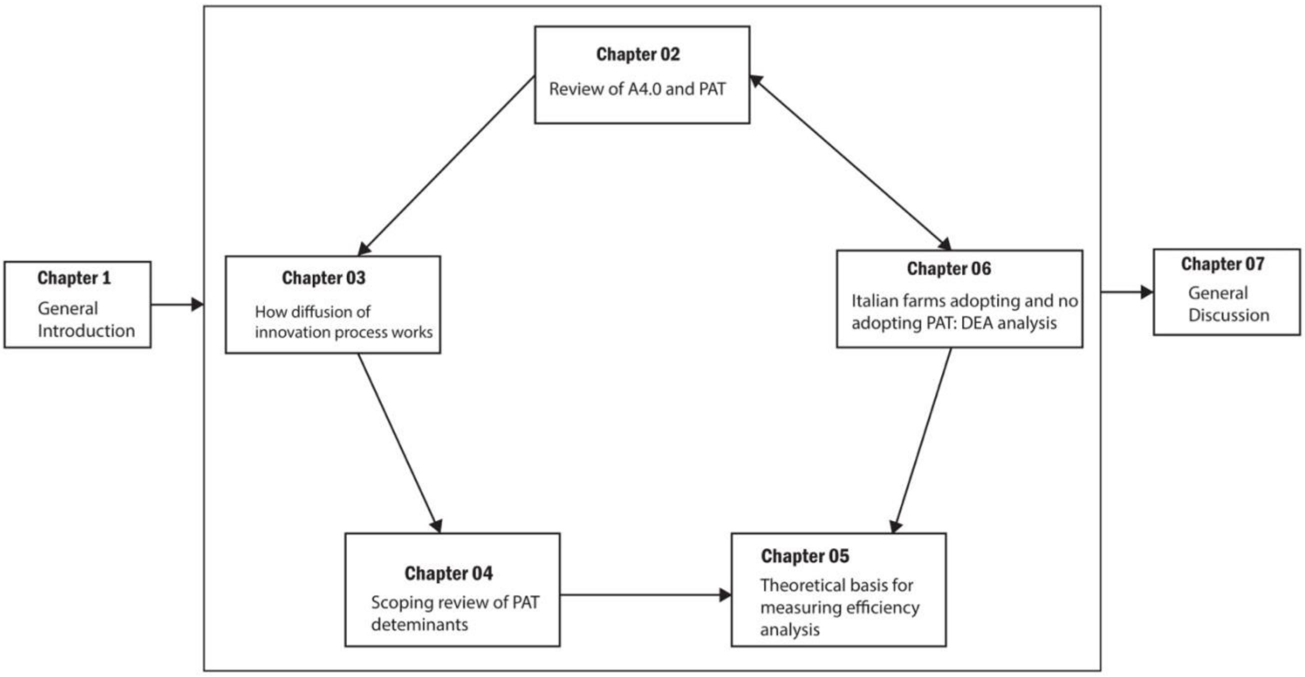

Figure 1.1 Thesis Outline

Chapter 2 Trends of Recent Innovation in Agriculture

2.1 Introduction

Agriculture is widely recognized as a crucial endeavor for human sustenance, as it supplies food, animal feed, fibers, fuel, and raw materials. The global population is projected to exceed 8 billion individuals by 2025 and almost 10 billion by 2050. This demographic surge is anticipated to substantially increase the demand for several essential human needs, particularly food, in terms of both quantity and quality. In order to meet these requirements, there must be a 60-70% increase in global food production. Moreover, the susceptibility of agricultural systems to weather conditions will escalate as a result of the heightened occurrence of extreme events, such as heatwaves, cold snaps, droughts, and heavy rainfall, which are linked to climate variations, soil deterioration, environmental contamination, and the scarcity of natural resources. Projected climate changes are expected to exacerbate current climate-related risks and introduce new ones, underscoring the importance of implementing effective management strategies to address emerging environmental concerns. Hence, there is a significant apprehension regarding the worldwide important trends and issues that would impact both the agricultural and food industries in the forthcoming decades. An evident illustration of this is the European Green Deal, which encompasses a collection of policy solutions with the objective of positioning Europe as the first continent to attain carbon neutrality by 2050, through the implementation of a sustainable growth strategy that encompasses all economic sectors. Within this framework, the "Farm to Fork" approach serves as the fundamental basis of the European Green Deal, with a specific emphasis on ensuring equitable agri-food systems for a smooth shift towards a sustainable circular economy. The ability to increase agricultural production in an environmentally sustainable manner is heavily reliant on advancements in technology and research in innovation. Digital technologies have the potential to significantly enhance agriculture growth by increasing the scale, efficiency, and effectiveness of farm production. The Food and Agriculture Organization (FAO) of the United Nations refers to this position as the "Digital Agricultural Revolution," while other sources refer to it as "Agriculture 4.0." (Kovács & Husti, 2018; Zambon et al., 2019).

The fourth industrial revolution began in the early 2010s and encompasses the utilization of state-of-the-art technologies, including Internet of Things (IoT), cloud computing, big data, and artificial intelligence (AI). These technologies are combined with sensors, robots, and digital twins, with a particular focus on machine learning (ML) techniques for advanced data analysis. Agriculture 4.0, in conjunction with the interconnection of mobile devices and other platforms, facilitates the generation and analysis of a substantial amount of data, which will be used as a basis for making informed decisions. Agriculture 4.0 is expected to have significant global benefits, including increased productivity and efficiency in agricultural and food systems, improved quantity, quality, and accessibility of agricultural products, adaptation to climate change, reduced food loss and waste, optimized use of natural resources in a sustainable manner, and ultimately, reduced environmental impact in the future (Sott et al., 2020).

2.2 Agriculture 4.0 Core Technologies

Whilst the utilization of data in the agriculture industry is not a unique idea, the innovation resides in the potential for sector digitalization. Another factor to consider is the caliber of the information acquired at the agricultural level and the tools employed to gather, store, analyze, oversee, and distribute this data. Recent advancements in sensor technology have enabled farmers to continuously monitor precise parameters in real-time, while robotics have facilitated more efficient automation of agricultural activities. Furthermore, the accessibility and affordability of computing power have facilitated the development of novel decision-support technologies to enhance agricultural management. Therefore, this section provides an overview of the functions of technologies that have been stated before as commonly utilized in the context of Agriculture 4.0 (Rose et al., 2021).

2.2.1 Internet of Things

The Internet of Things (IoT) encompasses a network of interconnected computing devices, sensors, appliances, and machines linked via the internet, each possessing distinct identities and capabilities for remote sensing and monitoring. The IoT reference architecture comprises six layers: the perception layer (hardware devices), network layer (communication), middleware layer (device management and interoperability), service layer (cloud computing), application layer (data integration and analytics), and end-user layer (user interface). In the agricultural context, IoT devices at the physical layer collect data pertaining to environmental and crop parameters, including temperature, humidity, pH value, water level, leaf color, fresh leaf weight, etc. The transmission of this data occurs in the network layer, the structure of which depends on the choice of communication technologies suitable for factors such as field size, farm location, and farming method. For example, ZigBee, LoRa, and Sigfox are commonly used in outdoor fields due to their cost-effectiveness, low energy consumption, and ample transmission range. The integration of IoT in agriculture aims to equip farmers with decision-making tools and automation technologies that seamlessly amalgamate knowledge, products, and services to enhance productivity, quality, and profitability (Shi et al., 2019).

2.2.2 Cloud Computing

Cloud computing is currently evolving as a commercial internet-based infrastructure that offers hardware, infrastructure, platform, software, and storage services to different Internet of Things (IoT) applications. Cloud computing has become increasingly popular in the agricultural industry in recent decades. It offers affordable data storage services for agricultural information, including text, images, videos, and more. This significantly reduces storage costs for agricultural businesses. Additionally, cloud computing provides advanced computing systems that can process large amounts of data and convert it into useful knowledge. This is particularly beneficial as farmers may struggle to make informed decisions due to technical limitations. Furthermore, cloud computing offers a secure platform for the development of agricultural Internet of Things (IoT) applications. This method can be regarded as a crucial instrument in the administration of agricultural enterprises, as it aids farmers in enhancing agricultural operations on their farms. Cloud computing, while offering numerous advantages, nevertheless has certain drawbacks. IoT applications are expected to produce substantial amounts of data, potentially including private data, and deliver quick responses. Nevertheless, network latency is a challenge for cloud computing in managing these applications, as they necessitate a continuous flow of information between devices and the cloud, making it impractical at times (Bonomi et al., 2012).

2.2.3 Artificial Intelligence in Agriculture

Artificial intelligence (AI) involves the development of theory and computer systems capable of performing tasks requiring human intelligence, such as sensorial perception and decision-making. Combined with Cloud Computing (CC), Internet of Things or also known as IoT, and big data, AI, particularly in the facets of machine learning (ML) and deep learning (DL), is regarded as one of the key drivers behind the digitization of agriculture. These technologies have the potential to enhance crop production and improve real-time monitoring, harvesting, processing, and marketing. Several intelligent agricultural systems have been developed that use ML and DL algorithms to determine various parameters like weed detection, yield prediction, or disease identification (Talaviya et al., 2020).

2.2.4 Machine Learning in Agriculture

Machine learning (ML) techniques are broadly classified into three categories: 1) supervised learning (linear regression, regression trees, non-linear regression, Bayesian linear regression, polynomial regression, and support vector regression), 2) unsupervised learning (k-means clustering, hierarchal clustering, anomaly detection, neural networks (NN), principal component analysis, independent component analysis, apriori algorithm and singular value decomposition (SVD)); and 3) reinforcement learning (Markov decision process (MDP) and Q learning). ML techniques and algorithms are implemented in the agriculture sector for crop yield prediction, disease, and weed detection, weather prediction (rainfall), soil properties estimation (type, moisture content, pH, temperature, etc.), water management, determination of the optimal amount of fertilizer, and livestock production and management (Liakos et al., 2018).

2.2.5 Deep Learning in Agriculture

Deep learning (DL) represents the extension of classical ML that can solve complex problems (predictions and classification) particularly well and fast because more “depth” (complexity) is added into the model. The primary advantage of DL is feature learning which involves automatic extraction of features (high-level information) from large datasets. Different DL algorithms are convolutional neural networks (CNNs), long short term memory (LSTM) networks, recurrent neural (RNN) networks, generative adversarial networks

(GANs), radial basis function networks (RBFNs), multilayer perceptron (MLPs), feedforward artificial neural network (ANN), self-organizing maps (SOMs), deep belief networks (DBNs), restricted Boltzmann machines (RBMs), and autoencoders. In the agriculture sector, DL algorithms are mostly used to solve problems associated with computer vision applications that target the prediction of key parameters, such as crop yields, soil moisture content, weather conditions, and crop growth conditions; the detection of diseases, pests, and weed; and the identification of leaf or plant species (Kamilaris & Prenafeta-Boldú, 2018).

2.2.6 Decision Support System

Data-driven decision support (DSS) is a software tool that assists users in efficiently and effectively utilizing intricate data to enhance their decision-making procedures. Consequently, both unprocessed data and the results of analytical tools can be transformed into knowledge and displayed in a user interface in a way that can be easily understood. A Decision Support System (DSS) is an essential tool in various sectors, including the agricultural sector. This sector is particularly suitable for utilizing a DSS due to the inherent complexity of agricultural activities, which involve numerous physical, chemical, and biological processes. Effective management of these activities necessitates the processing of substantial amounts of data. A Decision Support System (DSS) can enhance the decision-making process by assisting decision-makers in making more efficient choices, particularly when confronted with ambiguous and intricate data. One distinguishing feature of an agricultural Decision Support System (DSS) is its generally limited level of autonomy. Farmers have complete accountability for making ultimate decisions, namely actions, by assessing the suggestions/instructions given by the DSS, which can exhibit a certain level of autonomy within well-defined system limits (Zhai et al., 2020).

2.2.7 Digital Twins in Agriculture

Digital twin (DT) is a dynamic virtual replica of a real-life (physical) object of which it mirrors its behaviours and states over multiple stages of the object's lifecycle by using real-world data, simulation, and machine learning models, combined with data analytics to enable understanding, learning, and reasoning. A complete description of the DT concept for any physical system requires consolidation and formalization of various characteristics, including the physical and virtual entities, the physical and virtual environments, the metrology, and realization modules that perform the physical to virtual and the virtual to physical connection or twinning, the twinning and twinning rate, and the physical and virtual processes (Verdouw et al., 2021).

2.2.8 Big Data Analytics

The emergence of IoT technology has enabled the gathering of data at every phase of farming, leading to the production of progressively bigger quantities of data. However, the agriculture sector is currently underutilizing this data, which presents a significant opportunity for transformative innovation based on data analysis. This innovation can lead to more efficient and sustainable production and consumption practices in the long run. Big data analytics may significantly contribute to the conversion of data into enhanced value for agri-food stakeholders. This is achieved by its ability to rapidly aggregate, process, and visualize extensive and intricate datasets. The literature commonly defines big data using five dimensions: volume, velocity, variety, value, and veracity. The utilization of large-scale, diverse data from several sources in real-time and past records, along with advanced data analysis, prediction, and monitoring abilities, is anticipated to bring about significant transformations in farm management and operations. This will facilitate the ongoing enhancement of business models. In addition to its more conventional uses, such as improving agricultural output by determining the best factors (such as temperature and rainfall) based on extensive historical data from multiple locations, big data analytics also enables exploration of more intricate and less frequent scenarios (Wolfert et al., 2017).

2.2.9 Precision Agriculture Technologies

The International Society of Precision Agriculture states that Precision Agriculture Technologies (PATs) are central to the fourth revolution in farming technology. Precision Agriculture is a management approach that involves collecting, processing, and analyzing data related to time, space, and individual factors. This data is then combined with other information to make informed decisions that improve the efficiency, productivity, quality, profitability, and sustainability of agricultural production.(Lezoche et al., 2020).

2.2.9.1 Precision viticulture

Vineyards exhibit significant variation resulting from structural elements such as pedo-morphological characteristics, as well as other influences such cropping strategies and seasonal weather patterns. The variation in this factor leads to distinct physiological reactions in the vines, which in turn have a direct impact on the quality of the grapes. Vineyards necessitate precise agronomic management to meet the actual requirements of the crop, considering the spatial heterogeneity present within the vineyard. The implementation of novel technology in vineyard management enhances production efficiency and quality while simultaneously mitigating the environmental footprint. Advancements in technology have facilitated the creation of practical tools that aid in the surveillance and management of several elements of vine growth. Remote and proximal sensing sensors are powerful investigative tools for assessing the status of vineyards, including factors such as water and fertilizer availability, plant health and pathogen attacks, and soil conditions. Precision viticulture aims to utilize a diverse array of data to accurately represent the spatial variability of vineyards with great detail. It then offers recommendations to enhance management efficiency in terms of quality, production, and sustainability (Santesteban, 2019).

2.2.9.2 Geolocation

Georeferencing is the procedure of determining the correlation between spatial data and its geographic coordinates. This enables a comparative analysis of various spatial data collected in the vineyard, including soil physical characteristics, crop production, and water or fertilizer levels. The Global Positioning System (GPS) is a satellite-based navigation system that offers users precise and speedy information about their 3D position (x, y, z). A GPS receiver determines its location on Earth by utilizing data from at least four satellites. This method typically provides an accuracy range of 3-15 meters. However, differential techniques enhance the precision to the centimeter level by employing a network of stationary reference stations on the ground. These stations correct the positions indicated by the satellite systems, which have known fixed positions. This GPS technology is valuable for carrying out operations that demand exceptional accuracy, such as creating detailed maps of crops, operating self-driving farm vehicles, collecting soil samples, and distributing fertilizers and pesticides at varying rates (Tisseyre & Taylor, 2005).

2.2.9.3 Satellite

Precision farming has utilized satellites for more than four decades, starting with the launch of Landsat 1 into orbit in 1972. The device was outfitted with a multispectral sensor and offered a spatial resolution of 80 meters per pixel, with revisit intervals occurring typically every 18 days. Landsat 5 was deployed in 1984 and acquired images in the blue, green, red, near-infrared, and thermal spectral bands with a spatial resolution of 30 meters. The initial utilization of remote sensing in precision agriculture took place when Landsat imagery of exposed soil was employed to assess geographical distributions of soil organic matter content. Meanwhile, other continuing initiatives were undertaken to develop satellite imaging systems with improved spatial resolution and faster revisit cycles. The spatial resolution of imaging systems has undergone tremendous improvement, progressing from 80 meters with Landsat to sub-meter resolution with GeoEye and WorldView. Additionally, the frequency of image capture has increased from 18 days to 1 day with the introduction of new satellite platforms, accompanied by notable enhancements in sensor capabilities (Matese et al., 2015).

2.2.9.4 Aircraft

Aircraft have been employed in precision viticulture to accurately map expansive areas. This approach enables surveys to be conducted with greater adaptability, while also benefiting from the aircraft's extended flying range and capacity to transport substantial cargoes. The resolution of the final image on these platforms surpasses that of satellite platforms, achieving a ground-level detail of less than 10 m, which varies according to the altitude of the flight. Nevertheless, the implementation of these monitoring systems in VP has been limited due to the existence of intermediate organizations that provide this service, hence limiting the freedom to acquire time. Another limitation, in addition to the high expense, is the infeasibility of flying non-certain regions. While these technologies have some utility, their limited usage is hindered by constraints that make them impractical and complex. Additionally, the availability of new instruments with improved spatial resolution and user-friendliness, along with their low cost, is likely to diminish the use of traditional agricultural practices (Bonilla (Bonilla et al., 2013).

2.2.9.5 Unmanned Aerial Vehicle (UAV)

The advancement of technology in automation has introduced a new solution for remote monitoring in precision viticulture, namely UAVs. These aircraft, whether fixed-wing or rotary-wing, have the ability to fly without human intervention. Occasionally, they are erroneously referred to as "drones" because of their monotonous, low, and dull sound like the buzzing of a male bee. Unmanned Aerial Vehicles (UAVs) can be operated by a pilot on the ground within their line of sight or can navigate independently along a predetermined path using a sophisticated system of flight control sensors (including gyros, magnetic compass, GPS, pressure sensor, and triaxial accelerometers) that are controlled by a microprocessor. These platforms can be outfitted with a variety of sensors, enabling a diverse array of monitoring operations. The unique characteristic of utilizing UAVs in remote sensing is their ability to achieve high spatial ground resolution, measuring in millimeters. Additionally, UAVs offer the advantage of flexible and timely monitoring, thanks to reduced planning time. The aforementioned characteristics render it well-suited for vineyards of moderate to modest dimensions (1–10 ha), particularly in regions with significant fragmentation resulting from heightened heterogeneity (Rejeb et al., 2022).

2.2.9.6 Sensors

Sensors play a crucial role in the Internet of Things (IoT) concept, thanks to technological advancements that enable their size reduction, increased intelligence, and reduced cost. Wired and wireless sensors have become extensively utilized in the agriculture industry in recent years. They have a vital function in agricultural activities, as they gather data on plants, animals, and the environment. They are an essential technology for implementing IoT in agriculture. The management of spatial and temporal variabilities, which greatly impact agricultural production, can primarily be achieved through two methods: the map-based approach and the sensor-based approach. Both methodologies entail the use of fixed or portable sensors and necessitate extensive data gathering and analysis in order to optimize the utilization of agricultural resources, resulting in enhanced crop yield and ecological sustainability (Barbedo, 2019).

2.2.9.6.1 Wireless Sensor (and Actuator) Networks

Wireless sensor networks (WSNs) have become a prominent trend in recent years due to their extensive use in many agricultural applications, aiming to enhance conventional farming practices. Wireless sensor networks have three primary functions: (a) sensing, which involves collecting data; (b) communication, which involves exchanging information across network components; and (c) computation, which involves employing hardware, software, and algorithms to process data. A wireless sensor and actuator network (WSAN) is a type of wireless sensor network (WSN) that includes an additional component called an actuator. An actuator is a physical device, such as lamps, fans, pumps, valves, or irrigation sprinklers, that is responsible for interacting with the environment. These networks consist of multiple sensor and actuator nodes that are interconnected by wireless links. In general, these nodes consist of multiple components, each with its own specific function, such as sensing, control, processing, communication, and power (Singh et al., 2022).

Today, WSNs and WSANs are being used in multiple applications within the context of Agriculture 4.0 to enhance agricultural methods. These technologies have facilitated the real-time monitoring of several parameters of interest, including water parameters, soil properties, and atmospheric conditions. This has allowed for timely and appropriate responses in the field. As a result, they enhance efficiency, productivity, and profitability in many agricultural production systems by lowering inputs such as water and agro-chemical products. They also help mitigate waste and minimize negative environmental consequences (Ojha (Ojha et al., 2015).

2.2.9.7 Remote sensing

Remote sensing is a method that uses platforms to get detailed information about crops or items that are far away from a sensor. This is done by measuring the electromagnetic radiation that is emitted, reflected, or transmitted by these crops or objects. Remote sensing systems promptly offer a depiction of grapevine morphology, dimensions, and vitality, enabling the evaluation of the heterogeneity within the vineyard. This is a remote image acquisition technique that captures images of a vineyard using various levels of detail. It is capable of describing the vineyard by detecting and recording the sunlight that is reflected from the surface of items on the ground. Remote sensing data enables the description of plant physiology through the calculation of vegetation indices, such as the widely recognized normalized difference vegetation index (NDVI). This index takes advantage of the distinct reactions of vegetation to the visible (red) and near-infrared spectral bands, which are closely linked to the condition of crops. The reflectance of the canopy, namely in the visible and near-infrared bands, is greatly influenced by both the structural (leaf area index) and biochemical features (chlorophyll concentration) of the canopy. (Di & Yu, 2023).

2.2.9.7.1 Remote sensing applications

Remote sensing is primarily used in precision viticulture for reflectance spectroscopy. This technique involves measuring the reflection of electromagnetic radiation at various wavelengths, specifically in the visible region (400–700 nm), near infrared (700–1,300 nm), and thermal infrared (7,500–15,000 nm). The correlation between the intensity of the reflected and incident radiant flux is unique to each surface type. The spectral reflectance of an object, such as a crop or soil, is referred to as its "spectral signature". It is graphically depicted on an XY graph, where the reflectance value is plotted on the vertical axis (ordinate) and the wavelength of the spectrum is plotted on the horizontal axis (abscissa).

The predominant categories of sensors have the ability to detect any changes in transpiration or photosynthetic activity occurring on the surface of a leaf. Thermal sensors are employed for the remote measurement of leaf temperature. This temperature rises in response to water stress circumstances, leading to stomatal closure. Stomatal closure serves to decrease water loss but also disrupts the cooling effect of evapotranspiration. Changes in photosynthetic activity are associated with the nutritional state, health, and vitality of plants, and can be identified using multispectral and hyperspectral sensors. Leaf reflectance is determined by various factors in specific regions of the electromagnetic spectrum. In the visible region, the presence of photosynthetic pigments like chlorophyll a, chlorophyll b, and carotenoids influences leaf reflectance. In the near infrared region, the size and distribution of air and water within the leaf structure play a role. In the infrared region, the presence of water and biochemical substances such as lignin, cellulose, starch, protein, and nitrogen affect leaf reflectance (SAT, 2023).

2.2.9.7.2 Proximal Sensing

Proximal sensing utilizes a range of measuring technologies where the sensor is in close touch or proximity to the thing being measured. Proximal sensors, as defined, are typically optical or touch sensors. A proximal sensor is often characterized by a maximum range of two meters, meaning that it can detect objects within this distance. Proximal sensors enable the collection of georeferenced data on spatial variability with high levels of accuracy and precision. The proximity of the sensor to the crop or soil enables exceptional resolution of the images or measured data, resulting in this feature. Proximal sensing can involve point-type measurements, such as using optical contact sensors to determine the nutritional and physiological condition of the vine. This includes analyzing the levels of specific leaf pigments and nitrogen status. To evaluate the physiological and nutritional condition of the vineyard, there are two types of systems available: monoparametric sensors, which measure specific factors such as chlorophyll content, and multiparametric devices that analyze multiple parameters simultaneously. The instruments utilize the physical principle of fluorescence, which refers to the ability of some compounds, like chlorophyll, to release absorbed electromagnetic radiation as light energy dissipation. Fluorimeters are the devices used to conduct this research. They measure the absorption and transmission of radiation by the leaf. Additional varieties of proximal sensors utilized in precision viticulture encompass non-contact sensors that can be manually carried or put on a tractor, eliminating the need for direct contact with the crop (Yu et al., 2021).

2.2.9.8 Soil monitoring

A crucial use of innovative techniques in precision viticulture is the close monitoring of soil variability, which involves the utilization of a diverse array of sensors. Mobile platforms outfitted with soil electromagnetic sensors and GPS can continuously measure the apparent electrical conductivity of the soil.

It is a metric that has a strong correlation with several soil parameters, including texture, depth, water retention capacity, organic matter concentration, and salinity. The sensors employed for this particular test are either invasive electrical resistivity sensors or noninvasive electromagnetic induction sensors. The first form, known as electrical resistivity, is utilized to regulate the resistivity and, consequently, the conductivity of a specific volume of soil. This is achieved by creating electrical currents and subsequently detecting the potential changes. The electromagnetic induction sensors operate by generating a magnetic field that induces an electrical current in the ground. This current, in turn, produces a second magnetic field that is directly proportionate to the soil's conductivity. The sensor measures this conductivity. Additionally, there are recently created sensors designed specifically for mobile platforms. These sensors are capable of measuring pH, ionic nitrogen, and potassium concentration. They can also detect near-infrared and mid-infrared spectra, as well as utilize ground penetrating radar and radiometers. The soil properties are crucial in the cultivation of vines, as understanding the geographical diversity of soil qualities within a vineyard helps enhance our comprehension of the variety in grape physiological responses (Ammoniaci et al., 2021).

2.2.9.9 Crop monitoring

Various vineyard monitoring systems have been created to effectively observe the canopy side along the rows. These systems also include a GPS system to accurately record the geographical location of the data. Zhang et al. (2021) discuss some potential applications of agricultural sensors. An instance of such sensors is GrapeSense, which acquires a high-frequency digital image of the side of the canopy, gathering data on the height and texture of the vines along the row. These sensors are specifically intended to be attached to machinery and tractors, enabling the collection of geographical data during routine vineyard maintenance. Another evolving option is the utilization of Light Detection and Ranging (LiDAR) sensors, which may produce a georeferenced 3D representation of individual plants and generate maps that show the spatial variations in canopy volume, which is directly linked to the Leaf Area Index (LAI) (Tardaguila et al., 2021)

2.2.9.10 Yield and Quality Monitoring

Many approaches have been devised to acquire georeferenced yield data, particularly when incorporated into mechanical harvesters. These instruments empower the farmer to accurately measure and analyze the productivity of the vineyard with an unprecedented level of detail. The yield maps generated by these sensors serve as a valuable tool for assessing the efficacy of vineyard management strategies. The non-destructive monitoring of grape quality parameters relies on optical sensors that are specifically built as portable devices. These instruments are carried by an operator and utilized to perform georeferenced measurements in close proximity to the grapes (Ozdemir et al., 2017).

2.2.9.11 Variable Rate Technologies (VRTs)

VRT (Variable Rate Technology) in precision viticulture enables the precise differentiation of agronomic management and the timely and spatially targeted dosing of inputs. This method utilizes software that can integrate the positional data acquired from a GPS module with customized prescription maps for each individual procedure. The simultaneous advancement of standardized electronic communication in agricultural machinery has enabled the linkage between tractors and equipment. Significant endeavors have been undertaken to establish global standards for governing the communication protocols and information exchange among sensors, actuators, and software produced by various vendors. Research on VRT has investigated several application strategies, including as targeted distribution of nutrients and insecticides and optimized pruning techniques. The variable-rate strategy potential is determined by the advancements in vegetation monitoring technologies and high-performance atomization devices. The application of site-specific vineyard management seeks to move away from the notion of the vineyard as a unified area and instead proposes managing individual parcels and even smaller sub-parcels (Matese et al., 2015).

2.2.9.12 Robotics

The field of robotics has gained significant attention in agriculture in recent years, with robots being employed to automate various practices in this sector. These practices include crop scouting (monitoring and analyzing plant characteristics), planting and harvesting, water supply management, targeted spraying, environmental monitoring, weed and pest control, disease detection, pruning, milking, and sorting. UAVs and UGVs are mentioned earlier in relation to remote sensing. It is crucial to highlight that they can also be directly utilized in the fields to carry out specific agricultural duties. In industrial applications, fixed robots are commonly used, but in the field of agricultural, mobile robots can offer greater advantages. Their ability to traverse diverse terrains and reach remote landscapes, thereby covering expansive agricultural areas, while automating many agricultural operations, is considered highly promising for enhancing agricultural management (Roldán et al., 2018).

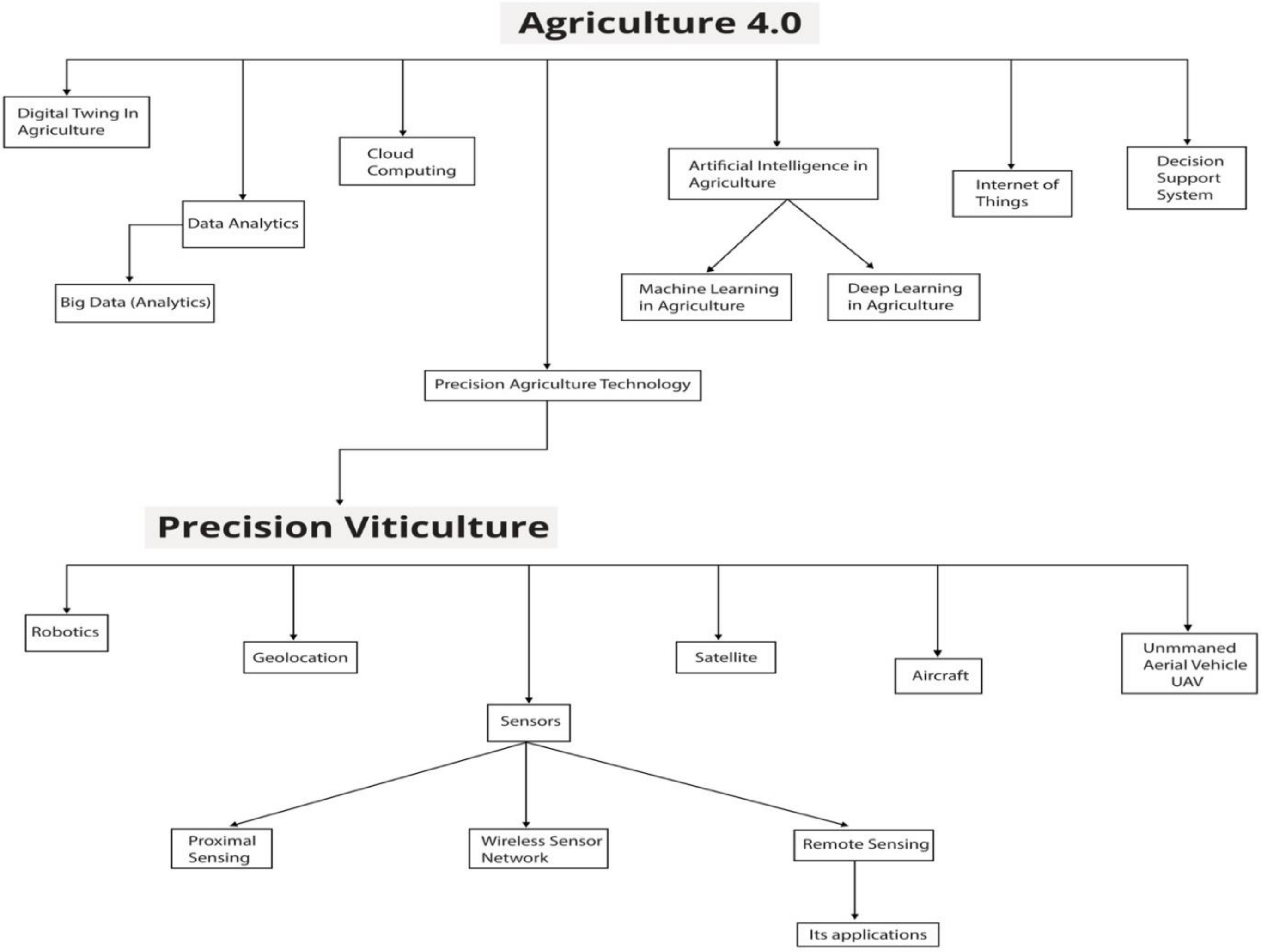

Figure 2.1 Overview of Agriculture 4.0 Technologies (own elaboration)

Chapter 3 Diffusion of Innovations in Agriculture

3.1 Introduction

Technology has a crucial role in enhancing the efficiency of agricultural resources. The practical use of technology derived from research or study is crucial for its effectiveness, particularly in endeavors aimed at empowering farming communities. Hence, it is imperative to develop a framework that takes into account the integration of innovation and the spread of technology in the agricultural industry. Technological and innovative decision-making Adoption is the sequential process via which an individual or decision-making unit becomes aware of an invention, evaluates it, and ultimately decides whether to adopt or reject it. Following the decision, the individual or unit then applies the ideas and confirms their choice (Kabunga et al., 2012).

Agricultural operations encompass several forms of innovations, which are inherent in their processes (Campos, 2021). These encompass a variety of advances, ranging from the adoption of traditional methods to intricate technology advancements (Moglia et al., 2018). Numerous innovations have a significant impact on various sectors and sub-sectors of the value chain that are crucial for agricultural development. These innovations include the implementation of agricultural technologies and inputs, as well as structural innovations like novel forms of organization and cooperation (Hannus & Sauer, 2021)

Diffusion and acceptance of inventions are sometimes used interchangeably, yet they are distinct ideas. Diffusion of innovations is the transmission of an innovation through certain channels within a social system over a period of time (Rogers, 2003). The term "adoption" pertains to the act of embracing or dismissing new ideas, whether it be by individuals or organizations (Kee, 2017). Nevertheless, as adoption inherently encompasses diffusion, we shall employ the overarching concept of dissemination and adoption of innovations, specifically focusing on their implementation in the field of agriculture. Existing literature consistently affirms that the adoption and spread of innovations in agriculture yield economic and environmental sustainability advantages, as supported by studies conducted by Aguilar-Gallegos et al. (2015) and Vollaro et al. (2019).

Innovation in agricultural technology Diffusion is an integral component of the process of technological innovation diffusion. Diffusion is the dissemination of new agricultural technology, inventions, successes, etc., from the point of origin to the surrounding area, where it is embraced and utilized by the majority of farmers and agriculture-related enterprises. The primary objective of dissemination is to achieve the commercialization of agricultural products through the adoption of agricultural technology. Agricultural technology innovation differs fundamentally from industrial technology innovation, with the former encompassing a wider range of themes compared to the latter. The objective of agricultural innovation exhibits the features of public goods or quasi-public goods. The process of agricultural innovation is characterized by discontinuity and a relative independence of innovation links. The user system of agricultural innovation possesses distinctive qualities, etc. Hence, the dissemination process of agricultural technology innovation involves many systems (Hasler et al., 2016).

3.2 Models Utilized in the Process of Adopting Innovation

Models offer a systematic framework for understanding adoption and enable the examination of the effects of many factors on the adoption process. Adoption models serve three main purposes: (a) to visually demonstrate the functioning of the system and identify the main factors that influence it, (b) to make quantitative predictions about the results that can be expected from the system, and (c) to systematically examine the uncertainty associated with the factors that drive the system and their impact on the outcomes. Adoption models can be classified into two main categories: theoretical or conceptual models and numerical models. Conceptual models employ flow diagrams or algebraic equations to identify adoption determinants and elucidate their interconnections and impacts, without necessarily aiming to quantify them. Numerical models are typically constructed using conceptual models in order to quantify the variables and determine the size of the relationships depicted in the conceptual models. Consequently, numerical models can be employed to authenticate a conceptual model, which serves as a concise and comprehensive representation of scientific information (Hameed et al., 2012).

3.2.1 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB), introduced by (Ajzen, 1991), is a commonly utilized theoretical model for understanding behavior. It is derived from the Theory of Reasoned Action. According to the theory, conduct is influenced by intention, which is determined by attitude, subjective norms, and perceived behavioral control. Prior research has demonstrated that the Theory of Planned Behavior (TPB) is highly effective in elucidating farmers' behaviors related to soil conservation, proper utilization of fertilizers, implementation of straw incorporation techniques, adoption of Best Management Practices, and preservation of water resources.

Attitude pertains to an individual's favorable or unfavorable assessment of the outcomes of their particular actions. In general, the more robust the farmers' mentality, the more determined they are to carry out the activity. Attitude, in the context of this study, refers to the farmers' favorable or unfavorable assessment of the outcomes associated with the adoption of Green Control Technology (GCT). The majority of studies also corroborate the perspective that attitude is a significant determinant of adoption intentions. A subjective norm is the perception of social pressure exerted by the surrounding social system, including family members, friends, government departments, partners, etc., on an individual's decision-making process. It reflects how the individual's intentions are influenced by the expectations of other groups.

Perceived behavioral control is the individual's subjective impression of the circumstances that either facilitate or impede the execution of a specific behavior, reflecting their own perception of their ability to carry out that conduct. The perception mostly relies on farmers' awareness of their own time, energy, expertise, abilities, and financial resources. In general, individuals who believe they have more resources and opportunities to engage in an activity tend to have lower anticipatory barriers, higher perceived behavioral control, and stronger intentions to do the behavior. Perceived behavioral control in this study pertains to the subjective perception of farmers regarding their ability to adopt Green Control Technology (GCT). The research conducted by (Lou, 2022) demonstrated that the perceived ability to manage one's behavior had a favorable influence on tea growers' inclination to embrace GCT (Green Control Technology) (Bosnjak et al., 2020)..

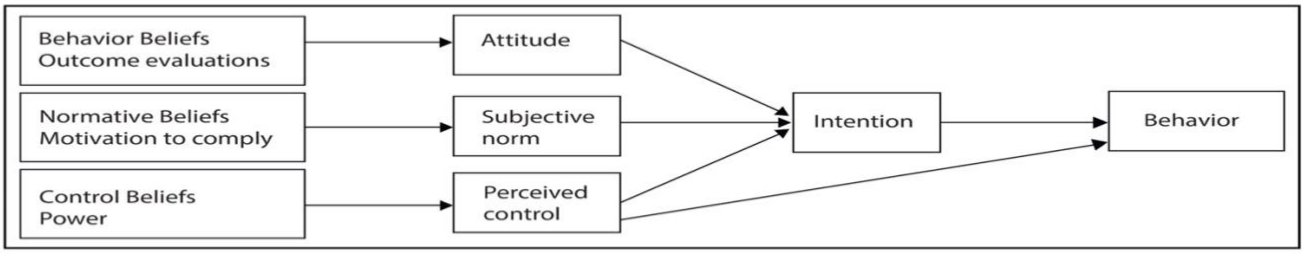

Figure 3.1 Representation of Theory of Planned Behaviour. Based on (Ajzen, 1991)

3.2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a conceptual framework designed to understand and predict the acceptance and usage of technology by users. TAM, which was first introduced in 1986 by Fred Davis and then further developed by Davis and Venkatesh, has become a crucial tool in the field of information systems and technology research. Its primary purpose is to evaluate how users accept and adapt new and emerging technologies. The model suggests that users' attitudes towards a particular technology, and thus their actual usage behavior, depend on their perception of how easy it is to use and how beneficial it is. The TAM framework identifies crucial elements: Perceived Ease of Use (PEOU) refers to users' subjective evaluation of the simplicity associated with utilizing a system or technology. This encompasses various variables such as the user interface, ease of learning, and simplicity of interaction. Perceived Usefulness (PU) refers to the users' perception that a technology improves their job performance or simplifies their tasks. The perception of usefulness has a substantial impact on users' attitudes towards adopting the technology. Attitude Toward Using (ATU) refers to the users' comprehensive assessment of a technology, which is shaped by their perception of how easy it is to use and how beneficial it is. Behavioral Intention to utilize (BI): The users' intention to utilize a technology is a direct result of their attitude and serves as a reliable predictor of actual system use. TAM primarily focuses on predicting behavioral intention, with the ultimate goal of comprehending and forecasting the actual usage of the system. Extensions, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), have incorporated supplementary elements to accommodate various circumstances. The application of TAM has been extensive across numerous domains, encompassing information systems, human-computer interaction, and consumer behavior. Researchers and practitioners utilize the Technology Acceptance Model (TAM) to create and assess interventions that encourage the acceptance and adoption of technology (Marangunić & Granić, 2015).

The Technology Acceptance Model (TAM) is a useful paradigm for comprehending the aspects that impact farmers' acceptance and utilization of new technologies in the agricultural sector, specifically in the context of agricultural innovation adoption. The adoption of innovations by farmers, such as precision farming technologies, remote sensing tools, or data-driven agriculture management systems, can be greatly influenced by their assessments of the technology's usability and perceived benefits. For example, if farmers see a new technology as easy to use and capable of improving their farming methods, they are more inclined to adopt it. Moreover, the presence of training and support, compatibility with current farming methods, and the perceived advantages in terms of higher yields or cost reduction are significant elements that influence farmers' attitudes and intents to embrace agricultural innovations. By employing the Technology Acceptance Model (TAM) in the agricultural domain, researchers and policymakers can acquire valuable understanding of the psychological and practical elements that influence the effective incorporation of technology into farming methods, thereby enhancing the sustainability and efficiency of agricultural systems (Alambaigi & Ahangari, 2016).

3.2.3 Diffusion of Innovation Theory

Rogers established the Innovation Diffusion Theory, which states that innovation is perceived as a novel idea or object by individuals, and its dissemination inside a certain channel or social system is referred to as diffusion. Moreover, this theory posits that the rate at which innovation spreads is influenced by factors such as comparative superiority, intricacy, congruence, testability, and perceptibility. Moore and Benbasat argued that the core of innovation diffusion lies in the gradual increase of individual adoption of innovation. They argued that the determining factor for the pace of dissemination is not the inherent qualities of the innovation, but rather relies on an individual's perception of those qualities. Relative advantage pertains to the extent to which users regard an innovation as an enhancement over the old technology, whereas complexity refers to the level of difficulty associated with using the innovation. Compatibility is the extent to which people think that an invention aligns with their beliefs, needs, and previous experiences. In general, people are more inclined to have a favorable intention to adopt technologies that have a high level of compatibility. This study defines compatibility as the farmers' subjective impression of the degree to which the General control

Technologies (GCT) align with their personal values, address their demands for pest and disease protection, and are consistent with their previous experiences in preventative and control measures (Miller, 2015).

Trialability pertains to the extent to which users think that an innovation can be tested and confirmed on a restricted scale. Generally, technologies that are readily testable by users will be more readily adopted than those that are challenging to test. Visibility pertains to the extent to which users can perceive the efficiency and efficacy of innovative transformation. (Peshin et al., 2009) conducted a study on the determinants of Indian farmers' adoption of Integrated Pest Management (IPM) and discovered that visibility plays a significant role in predicting farmers' adoption behavior.

Rogers' theory of innovation is widely regarded as the most well-supported and important theoretical framework for understanding the process of technological adoption in the field of agriculture. Rogers's perspective on the innovation process encompasses three distinct stages: innovative invention, development, and diffusion and adoption. Adoption is a component of the diffusion process. The adoption process pertains to an individual's choice to incorporate (or not) innovation into their life, whereas "diffusion" characterizes the spread of this adoption process throughout a population over a period of time. Rogers delineated four constituents of the process. The initial element is innovation, which can be defined by five distinct attributes: relative advantage (the perception of an individual regarding whether the innovation is superior or inferior to similar ideas), trialability (the extent to which the innovation is experimented with), observability (the perception of how easily accessible and visible the innovation is to an individual), complexity (the perception of how difficult it is to understand the nature of the innovation), and compatibility (the perception that a specific innovation is similar to existing or previous ideas). The second term pertains to communication channels, which are the means via which innovation knowledge is sent from one person to another. The third component is the social system, encompassing the contextual, cultural, and environmental factors in which innovation is situated and individuals are engaged. Time is the fourth component. The diffusion process, depicted as a Gaussian distribution, categorizes individuals into distinct adopter categories: innovators, early adopters, early majority, late majority, and laggards. Adopters can be categorized based on their socio-economic traits, personality features, and communicative behaviors. Innovation assumes that innovators exhibit a propensity for risk and embracing change, whereas the late majority tend to be wary, and laggards adhere to conventional practices. One of the socio-economic traits of innovators/early adopters is a greater degree of education, elevated social position, and engagement in larger and more specialized activities. In addition, they exhibit greater rationality, are focused on achieving outcomes, demonstrate a better level of social engagement, and maintain more frequent interactions with technical support personnel while also having greater access to information. When confronted with a new idea, individuals rarely embrace it quickly. Prior to making the adoption choice, individuals engage in a learning phase during which they gather information and maybe experiment with the innovation for a defined duration. The act of adopting is not an isolated occurrence, but rather the outcome of a complex series of stages. Rogers (1995) identified five steps in the adoption process: (i) Awareness: The individual becomes cognizant of the presence of the new practice/idea; (ii) Interest: The individual develops a curiosity and actively seeks additional information about it; (iii) Evaluation: The individual mentally assesses its applicability to their own circumstances; (iv) Trial: The individual puts it into practice, typically on a smaller scale; (v) Adoption: The individual makes a deliberate choice to continue utilizing the innovation in the future. This approach has faced numerous criticisms due to significant deficiencies identified in the area of scientific validation. Initially, it is important to note that there is a lack of definitive scientific data supporting the notion that adoption behavior, such as being an early adopter or a later adopter, is consistently consistent over an extended period of time. The attributes of the innovation do not suffice to elucidate the adoption behavior of humans, as it is contingent upon how individuals perceive them during the adoption process.

3.2.4 Motivational Model

Human behavior is driven by motivation, which is a psychological inclination to stimulate and sustain an individual's focus on a specific objective. Motivation serves as the foundation for both constructive and destructive human actions. Research on behavioral motivation has consistently been a prominent subject in the field of psychology. Theories such as the Expectancy-Value Theory, the Self-determination Theory, the Attribution Theory, and the Goal Theory, together with other motivation theories, have extensively examined motivation from various perspectives. Although numerous theories have been proposed regarding motivation, they generally concur that motivation can be classified into two distinct categories: intrinsic motivation and extrinsic motivation, which are determined by their origin, and both types of motivation play a role in the development of intentions. Extrinsic motivation is a form of motivation that arises from external factors or outcomes rather than from one's own behavior. Instances of extrinsic motivation encompass the acquisition of rewards, the avoidance of penalties, or the enhancement of job proficiency. This form of motivation is driven by the reinforcement value that arises from behavioral outcomes. This study subsequently tested the aforementioned concept by substituting perceived usefulness with external incentive. Davis et al. proposed that the perception of usefulness is a key driver of intentions and offers a solid explanation for the external value of adopting a behavior. The initiation of intrinsic motivation is triggered by the inherent mental needs that are largely fulfilled by the behavior's own attributes. Ryan and Deci hypothesized that most intrinsic psychological needs are comprised of autonomy, competence, and relatedness. Moreover, they proposed that the extent to which an individual perceives a particular behavior as fulfilling these three needs is strongly correlated with the level of their intrinsic drive for that behavior. Comprehending human motivation is a challenging endeavor as it necessitates unraveling the intricate network of circumstances that drive individuals to initiate, persist, and ultimately achieve their objectives. Motivational models, derived from psychological and behavioral theories, serve the objective of offering conceptual frameworks that enhance our comprehension of the intricacies of human motivation. This essay examines the fundamental elements commonly found in motivational models, offering insights into the varied nature of motivation by analyzing these components (Lai, 2017).

Various types of motivation revolve around the core human needs and desires. The models draw inspiration from Abraham Maslow's hierarchy of needs, which recognizes that individuals are motivated by a hierarchy of needs, starting from basic physiological necessities and progressing towards greater aspirations for self-actualization. Understanding this basic concept is essential for studying the intricate interplay among psychological, social, and environmental factors that contribute to the development of motivational processes. The Expectancy-Value Theory serves as a fundamental element in various motivational frameworks. It highlights the importance of individuals' expectations and the personal worth they assign to the results of their actions. According to this hypothesis, motivation is not solely determined by a desire for a certain outcome; instead, it is also influenced by the belief that one's efforts can result in success. Psychologists developed this notion. This idea is reinforced by incentive and reward systems, which acknowledge that the expectation of positive outcomes or the avoidance of negative consequences can serve as powerful motivators. The Self-Determination Theory (SDT) posits a notable distinction between two forms of motivation: intrinsic and extrinsic. The Self Determination Theory (SDT) posits that individuals are most effectively motivated when their actions align with their intrinsic values and interests. This idea highlights the importance of autonomy and competence. Cognitive Evaluation Theory, an extension of the Self Determination Theory (SDT), explores how external factors, such as feedback and social environment, impact an individual's intrinsic motivation. Goal-setting process Locke's thesis says that establishing specific and challenging goals can greatly enhance motivation and performance in the long run. Individuals are driven to exert effort towards the attainment of their goals when they possess well-defined objectives since they provide them with a distinct feeling of direction and purpose (Deci et al., 2017). Social Cognitive Theory, developed by (Bandura, 1989), introduces the concept of observational learning. This idea highlights the influence of observing the actions and outcomes of others on an individual's motivation.

(Csikszentmihalyi et al., 2005) Flow Theory examines the psychological phenomenon called "flow," characterized by profound involvement and absorption in an activity. An individual's optimal level of performance and motivation is achieved when they are presented with a task that aligns with their skills. The Attribution Theory focuses on comprehending the cognitive processes that underlie the interpretation and explanation of success and failure. These processes subsequently influence the future motivation and behavior of individuals. The Biopsychosocial Model is a holistic approach that acknowledges the interconnected impact of biological, psychological, and social factors on motivation. This model provides a comprehensive perspective on the diverse factors that influence motivational processes by considering the complex interaction among distinct variables.

3.2.4.1 The Role of Motivational Model in Agriculture

In the field of agriculture, where the difficulties are as varied as the crops that are grown, the function of motivational models becomes of the utmost importance in terms of comprehending and influencing the actions and behaviours of agricultural practitioners, farmers, and other stakeholders. As a multidimensional field, agriculture is comprised of intricate procedures that range from the growing of crops to the implementation of technology advancements and the implementation of sustainable practises. In order to give a lens through which these complexity can be completely analysed and addressed, a motivational model that is specific to agriculture is provided. The recognition of the inner and extrinsic motives that drive persons within the agricultural sector is the cornerstone of any model that seeks to serve as a source of motivation in the agricultural industry. It is essential to have a thorough understanding of the requirements and motivations of farmers in order to develop effective strategies that are tailored to the specific challenges and objectives that farmers face. Considerations of economic factors, such as financial stability and profit objectives, as well as inner motivations connected to a sense of accomplishment and purpose obtained from successful agricultural practices, are included in this category. When it comes to agriculture, the Expectancy-Value Theory, which is a foundational model of motivational models, finds resonance since it places an emphasis on the significance of expectancies and perceived values. If a farmer believes that new practices or technologies will result in favourable results, whether those outcomes are greater yield, cost-effectiveness, or environmental sustainability, then they are more inclined to adopt those practices or technologies. Furthermore, the perceived value that is associated to these outcomes is a significant factor that plays a vital part in determining the motivation to accept change.

The function of goal-setting theory becomes especially relevant when considered in the context of agricultural innovation. Farmers frequently establish objectives about crop yields, the optimization of resources, and the implementation of sustainable farming practices. A sense of direction and purpose in their agricultural endeavours can be fostered through the use of motivational models that are informed by goal-setting theory. These models can assist stakeholders in tailoring interventions that are in alignment with the objectives of farmers. As a conclusion, the function of motivational models in agriculture is extremely important in terms of navigating the intricacies of decision-making, goal-setting, and the adoption of technology within the sector. It is possible for stakeholders to design interventions that are congruent with the ideals and goals of agricultural communities if they have an awareness of the many reasons that farmers have and make use of those motivations. For this reason, motivational models are vital tools for the development of strategies that promote agricultural practises that are both sustainable and beneficial to the environment.

3.2.5 The ADOPT Model

The Adoption and Diffusion Outcome Prediction Tool, or ADOPT, is a conceptual model designed to explain the complex structure of technology adoption, with a specific focus on its use in the agricultural domain. The ADOPT framework was created as part of the Agricultural Model Intercomparison and Improvement Project (AgMIP). The objective of this is to encompass the intricate cause-and-effect linkages that influence the acceptability of agricultural advancements. The concept of adoption is of utmost importance in the ADOPT model. Adoption refers to the complex process of integrating new technologies and practices into the agriculture sector. The primary aim of ADOPT is to analyze the factors and conditions that contribute to two significant diffusion outcomes: the maximum level of adoption and the rate at which adoption occurs. This is the core of the organization's mission, which is to decipher the intricacies of the adoption process. The model takes into account 22 distinct factors. Each variable reflects a distinct element of the agricultural ecosystem that has a substantial influence on the trajectory of technology adoption. These variables encompass a diverse array of influences, such as personal characteristics, financial considerations, social interactions, and technological features, among various others. The ADOPT model provides a holistic view of the various factors that jointly shape the trajectory of innovation adoption in agriculture. This is achieved by including these variables into the structure of the model.

ADOPT is a collection of economic and sociological principles, and its theoretical constructs embody this amalgamation. The concept of relative advantage, originally drawn from the theory of innovation diffusion, is a basic element of this conceptual framework. The perceived superiority of an invention compared to current practices is a critical aspect in the decision-making process. The study of Relative Advantage is a parallel framework that examines the cognitive processes humans undergo to gain knowledge and understanding of the benefits provided by an invention.

The application of the ADOPT model to the sphere of agriculture brings about a distinct and noticeable impact. This offers researchers, policymakers, and other stakeholders a lens to observe the intricate process of technology adoption in the agricultural setting. ADOPT provides a comprehensive grasp of how cutting-edge farming technologies, ecologically responsible practices, and novel crop management methods are implemented and disseminated in the agricultural industry. Ultimately, the ADOPT model is a potent and flexible tool that offers valuable insights into the implementation of agricultural technologies. ADOPT not only clarifies the complexities of the adoption process, but also offers stakeholders a predictive framework to effectively navigate the ever-changing landscape of agricultural technology. This is achieved by capturing a wide range of factors and theoretical ideas.

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3.2.5.1 Relative Advantage

The primary catalyst for adoption in the ADOPT model is a significant superiority or benefit. The literature extensively supports theories pertaining to relative advantage in modeling, such as subjective expected utility theory, prospect theory, and multi-attribute utility theory. Extensive research has demonstrated that the primary factor motivating farmers to willingly adopt new agricultural practices is the presence of a comparative advantage. The ADOPT conceptual model defines relative advantage as the extent to which an innovation is seen as superior to the notion it replaces. This definition accommodates the incorporation of several factors that influence farmers' decision-making. The ADOPT model incorporates three decision maker's orientations (profit, environmental, and risk) that have the potential to impact the relative benefit of the technology or practice being analyzed across these three components (Pannell et al., 2011).

3.2.5.1.1 Learning of Relative Advantage

The ADOPT model includes learning as a significant aspect at a high level. The accept conceptual model, proposed by Lindner et al., delineates the characteristics and causal interactions that influence the probability of adopting an agricultural innovation and the duration between its availability and the decision to accept it. The discovery stage refers to the period during which the producer becomes aware of the innovation's existence. The evaluation stage is the time between awareness and the initial use of the invention on a trial basis. The trial stage is the period from the start of trial use to the acceptance of the innovation. The attributes of the invention and the attributes of the population of adopters have an impact on the duration it takes to accept an innovation. This process encompasses the stages of awareness, trialing, and adoption as described by Pannell et al. (2021).

3.2.5.2 The Role of ADOPT Model in Agriculture

The Agricultural Model Intercomparison and Improvement Project (AgMIP) is accountable for the creation of the ADOPT model, utilized for assessing the potential implementation of agricultural practices and technologies. If this is the model you are referring to, it aligns with the description you provided earlier, as it includes variables and aspects related to the application of agricultural technologies. The model likely incorporates aspects such as the comparative benefits of new agricultural technology, economic variables, and sociological characteristics that impact the acceptance of advances in the agricultural industry. In the context of agriculture, "adoption of innovations" refers to the process of embracing and integrating new farming practices, technology, and techniques. Farmers may accept innovative ideas for several reasons, such as to improve productivity, achieve cost-effectiveness, promote sustainability, and ensure compatibility with existing practices. The ADOPT model in agriculture can be a valuable tool for researchers and policymakers in the agricultural business to comprehend and forecast the patterns of technology adoption in the agricultural sector. It possesses the capacity to offer valuable understandings on the decision-making process that farmers undergo when adopting new practices or technology, as well as the spread of these innovations within agricultural communities (Pannell et al., 2011)

3.2.6 Information Flows Model

Lindner et al. (2018) described the fundamental steps involved in the time delay between the introduction of agricultural innovation and the decision of individuals to adopt it. These steps include the discovery stage, which is the period required for producers to become aware of the innovation's existence, the evaluation stage, which is the time taken from awareness to the initial trial use, and the trial stage, which is the duration from the start of trial use to the acceptance of the innovation. Lindner et al. proposed that information is of utmost importance in the three stages, highlighting variations in the type of information gathered. During the discovery stage, the producer actively seeks information regarding the existence of previously unknown innovations. The second and third stages involve collecting innovation-specific information about its attributes in order to make the decision to first trial it and then adopt it. During the evaluation phase, the information is obtained from sources outside the farm, whereas the information gathered during the trial period primarily comes from within the farm. Lindner et al. (2018) proposed that the progression from one stage to another is contingent upon the gathering of information and the efficiency of its processing. The discovery stage will conclude once the producer has thoroughly surveyed an adequate number of information sources to gain knowledge about the innovation. The evaluation stage concludes when the producer has gathered enough information from external sources to make a decision on whether to implement or not implement the invention. The amount of information needed to progress from each stage will vary based on the producer's assessment of the information's quality or dependability. The quality, in this instance, is assessed based on the degree of doubt over the pertinence of the information to their agricultural company. Lindner et al., (2018) proposed that the minimum amount of information required to transition from awareness to trial is influenced by the producer's pessimism and conservatism regarding their initial perception of the innovation's relative advantage, as well as their level of innovativeness, as suggested by Rogers.

The Information Flows Model is a foundational framework in communication theory that illuminates the intricate processes of generating, transmitting, and receiving information across many systems and situations. This model recognizes the complexity of information exchange in both directions and the dynamic interaction of multiple components within the communication process. It surpasses linear perspectives of communication. The Information Flows Model underscores the interactive nature of communication in its most basic form. It posits that communication is not solely the transmission of information in one direction, but rather a reciprocal interaction including senders, messages, channels, receivers, and the surrounding environment. This dual perspective aligns with the recognition that successful communication necessitates not just the conveyance of information but also its comprehension, thereby fostering a continuing and dynamic discourse. An essential element of the Information Flows Model is the examination of the multiple constituents that influence the dynamics of communication. The sender bears the burden of crafting a message specifically tailored for the recipient, given that they are the ones who initiated the contact. The choice of channel or medium through which the message is transmitted is a crucial component that influences the perception of information. Furthermore, the context in which communication occurs adds supplementary dimensions of significance, consequently influencing the interpretation of the message.

3.2.6.1 The Role of Flows Model In Agriculture

The Flows Model is crucial for comprehending and enhancing communication mechanisms in the intricate realm of agriculture. The Flows Model serves as a guiding framework for comprehending the dynamics of communication in this industry, where the exchange of information is a crucial element in decision-making, resource management, and the adoption of innovative procedures. The Flows Model in agriculture recognizes the bidirectional nature of communication at its core. A network characterized by the constant exchange of information consists of dynamic participants, including farmers, agricultural experts, researchers, and policymakers. This method recognizes that effective communication involves more than simply conveying information. It involves a two-way engagement where feedback and interpretation play crucial roles.

The Flows Model has various characteristics that are highly relevant to the agriculture industry. The elements encompassed in this context are transmitters, communications, conduits, recipients, and circumstances. The farmers, as senders, are responsible for composing communications regarding crop management, pest control, weather conditions, and other crucial matters. The selection of communication channels, whether they are traditional, agricultural extension services, or digital platforms, significantly influences how information is conveyed and received. The agricultural context introduces additional layers of complexity, hence complicating the communication process. Having a thorough understanding of the information being given is crucial due to the inherent attributes of agricultural cycles, seasonal variations, and regional differences. The Flows Model considers the surrounding environment when analyzing communication, therefore accounting for these subtle distinctions. This guarantees that communications are tailored to accommodate the challenges and opportunities that exist in different agricultural contexts. The Flows Model's ability to adapt to advancements in digital technology is particularly relevant in the modern agriculture industry. The growth of online platforms, agricultural applications, and precision farming technologies has altered the way farmers, researchers, and other stakeholders share information. Considering the advancements in digital technology, it is necessary to apply the Flows Model in a dynamic manner to comprehend how the speed, extent, and influence of information distribution are affected by certain technologies (Fountas et al., 2006).

The Flows Model is a framework used in sustainable agriculture to facilitate communication about environmentally friendly practices, conservation measures, and responsible resource management. Stakeholders are able to effectively convey the ecological, economic, and social advantages of sustainable farming, fostering a shared comprehension among members of the agricultural community and promoting collaboration. In conclusion, the Flows Model is an essential tool used to analyze the intricacies of communication in the agricultural industry. The objective of this model is to offer valuable perspectives on how effective communication can enhance decision-making, facilitate the adoption of innovation, and bolster overall resilience in the agriculture sector. This is achieved by comprehending the bidirectional, contextual, and dynamic characteristics of information transmission. The Flows Model is an indispensable tool for navigating the complex network of agricultural communication, even in the current era marked by rapid technical advancements and increasing emphasis on environmentally sustainable methods (Fountas et al., 2006).

3.2.7 Task-Technology Fitness Model

The task-technology fitness model highlights the significance of technology in bridging the gap between individual preferences and task characteristics. This model serves as a valuable reminder that in the field of agriculture, it is extremely probable that there currently exists a technology or practice that fulfills each task and thus provides advantages to the landowner. Hence, it is quite probable that any novel technology will serve as a substitute for the current one. The term "task" can be seen as a distinct action, such as harvesting, or it can also encompass an activity that occurs within the context of farming, such as irrigation within a specified water allocation limit. Agricultural conditions are always changing, necessitating a continuous evaluation of the effectiveness of existing methods. An "additional assignment" may develop when there are changes in farming conditions (such as the introduction of new environmental legislation), requiring the consideration of new technologies or techniques. Under conditions of relative stability, the introduction of new technologies or practices sometimes leads to only small, gradual enhancements in the performance of existing technology, such as the development of a new crop cultivar (Dissanayake et al., 2022).

The Technology Fitness Model is a comprehensive reference that offers a framework for evaluating and understanding the compatibility and effectiveness of technology in various contexts. This model plays a crucial role in navigating the complex process of integrating technology by providing insights into how well a technology matches the requirements, objectives, and capabilities of users and organizations. The Technology Fitness Model addresses the inherent relationship between technology and its users. It acknowledges that the successful implementation of technology is not solely determined by the capabilities and features of the technology itself, but rather is closely linked to how well the technology fits the needs and objectives of the users who are intended to use it. An integral component of the Technology Fitness Model is its consideration of the desires and needs of the users. A comprehensive examination of the specific functionality and features that users seek in a technology is necessary for this stage. Organizations can enhance user satisfaction and facilitate the integration of technology into existing workflows by aligning the technology with user desires and unique requirements. Compatibility is a crucial element inside the model architecture. Compatibility encompasses both the technical and organizational components of the problem. Regarding the technical aspect, it entails assessing the compatibility of the technology with the existing infrastructure and processes. Conversely, organizational compatibility examines how the technology aligns with the organization's culture, regulations, and processes. In order to guarantee the effective implementation and utilization of the technology, it is crucial to ensure agreement and coordination on both aspects. The Technology Fitness Model also considers the learning curve associated with new technology. By acknowledging this, it recognizes that the user's level of expertise and comfort with a technology are crucial factors in assessing its overall preparedness. Users are more likely to adopt and effectively utilize a technology that is user-friendly, accompanied by comprehensive training programs, and has a smooth learning curve (Dissanayake et al., 2022)

Furthermore, the model considers the variables of technology's flexibility and scalability. In the rapidly evolving technology landscape of today, a fitness review should not solely focus on the existing needs that are being fulfilled, but it should also anticipate the future needs that may arise. To achieve a longer and more sustainable lifespan in an organization, it is highly beneficial to have a technology that can easily accommodate growing demands and adjust to changing situations. Security and compliance are vital elements inside the Technology Fitness Model. There is no scope for bargaining when it comes to ensuring that a system meets stringent security standards and complies with relevant regulations. This is particularly true in areas where safeguarding data and ensuring privacy are paramount. Therefore, the model promotes firms to conduct a thorough examination of the security characteristics of a technology before employing it. The Technology Fitness Model assists organizations in selecting technologies that drive progress and offer a competitive advantage in the context of digital transformation and innovation. By providing a structured framework for assessing the suitability of technologies using a comprehensive set of criteria, it facilitates the process of making strategic decisions (Dissanayake et al., 2022)

3.2.7.1 The Role of Task-Technology Model In Agriculture

The Task-Technology Fit (TTF) Model is a significant framework that may be employed to assess and enhance the congruence between the agricultural activities and the technologies employed. Within the agricultural sector, the TTF Model serves as a crucial factor in assessing the degree to which technology supports and improves the many activities performed by farmers and stakeholders. This is particularly significant due to the emphasis placed on efficiency, precision, and sustainability. The TTF Model emphasizes the crucial role of technology-task compatibility in determining the effectiveness of technology implementation. In the field of agriculture, the TTF Model is essential for ensuring that selected technologies can effectively support a range of tasks, such as crop management and resource allocation. When it comes to the TTF Model, it is crucial to thoroughly analyze specific task requirements. Each agricultural work necessitates distinct capabilities and qualities from the corresponding technology. For example, precision farming involves using technology that provide up-to-date information on soil conditions and crop health. Harvesting operations may need using machines with advanced automated features. The TTF Model aims to facilitate the selection of solutions that can effectively solve the specific challenges encountered in the agricultural workflow. It achieves this by matching the features of technology with the unique requirements of the activity. Compatibility is a crucial element of the TTF Model, encompassing both its technological and organizational dimensions. From a technical standpoint, the model prompts an assessment of the extent to which the technology can seamlessly integrate with the existing infrastructure and procedures. Compatibility between technologies and agricultural tools, sensors, and equipment is crucial in the agricultural sector to ensure streamlined operations. The TTF Model promotes an assessment of the compatibility between the technology and the current agricultural practices, workflows, and overall objectives of the farming enterprise at the organizational level. This review is conducted to assess the compatibility of the technology. One of the factors considered by the TTF Model is the learning curve associated with new technology. When considering agriculture, which involves farmers with different levels of technological proficiency, it is crucial to choose technologies with user interfaces that are easily comprehensible and to offer comprehensive training programs. When a technology is tailored to align with the capabilities and expertise of its users, there is a higher probability of it being effectively embraced and leading to enhanced productivity. In the field of agriculture, ensuring data privacy, efficient farm management, and adherence to rules are crucial. Therefore, security and compliance, which are integral aspects of the TTF Model, hold significant significance. Prior to the use of technology in agriculture, it is imperative to assess the safety elements of the technology and ensure its compliance with industry and regulatory standards. To summarize, the TTF Model is a strategic framework that functions as a navigational tool for farmers and stakeholders in the agricultural industry. It offers a systematic approach to choosing and incorporating technology in a streamlined manner. The TTF Model enables the agricultural community to utilize technology as a catalyst for enhancing efficiency, fostering innovation, and promoting sustainable practices. This is achieved by considering the specific requirements of the task, ensuring compatibility, minimizing learning curves, providing flexibility, ensuring scalability, and prioritizing security (Goodhue & Thompson, 1995).

3.3 Importance of diffusion models in Agriculture

Diffusion models are crucial and serve a diverse role in the agricultural industry. They offer crucial perspectives on the procedures that farmers and other stakeholders undertake to embrace innovations, technologies, and practices. The significance of these models lies in their ability to unravel the intricacy of invention diffusion. Their role is to guide policymakers, extension agencies, and researchers in promoting sustainable agricultural development within the agricultural sector. This essay explores the importance of diffusion models in the agriculture industry. The usefulness of diffusion models in agriculture lies in their ability to provide a structured understanding of the adoption process, making them highly valuable. These models enable the implementation of targeted interventions by categorizing adopters into distinct categories based on their propensity to embrace innovations. An instance of such a model is the Diffusion of Innovations Model developed by Rogers. Stakeholders can create tailored strategies for different groups of farmers by recognizing the variability among them, which spans from early adopters to those who are slower to adopt new practices. Furthermore, diffusion models, such as the Bass Diffusion Model, emphasize the societal dimension of the innovation adoption process. The importance of social influence is highlighted by these models, which are especially valuable in the agricultural industry, as farmers often depend on interpersonal connections and networks for information. To build effective communication and extension campaigns, it is crucial to have a comprehensive grasp of the social network dynamics within the agricultural community. Additionally, it is important to identify the opinion leaders operating within that society (Hunter et al., 2008; Rogers, 1995).

Rogers' Five aspects Model provides a thorough framework for assessing the perceived attributes of innovations. It highlights the need of considering aspects such as relative advantage, compatibility, complexity, trialability, and observability. This enables the assessment of innovations in a thorough manner. In the agricultural industry, the adoption of new technology is significantly influenced by various aspects, such as economic feasibility, compatibility with existing procedures, and the convenience of conducting trials and observations. Diffusion models aid in evaluating and addressing the characteristics stated above to enhance the acceptability of innovations. The IDRC Model, which focuses on the stages of awareness, interest, evaluation, trial, and adoption, contributes to the strategic planning of extension services and development programs. This method recognizes the sequential nature of the adoption process, allowing for the smooth introduction of interventions at each stage. Hence, it serves as a guide that steers farmers through the multiple phases involved in the adoption of new practices or technologies. Another crucial aspect of the importance of diffusion models in agriculture is in their adaptability to various circumstances. Agricultural academics and practitioners might combine elements from many models to create customized frameworks that address the specific situations related to agricultural advancements. The flexibility of this approach allows for a comprehensive comprehension of the diverse factors that impact adoption, encompassing the individual, societal, economic, and environmental aspects (Neilson, 2001).

The utilization of social network models and agent-based models enhances the veracity and precision of diffusion forecasts. These models, which focus on the impact of social interactions and imitate individual behavior, respectively, contribute to more precise predictions. Gaining insights into the intricacies of social networks is advantageous in the field of agriculture, where there is a substantial flow of information and guidance among farmers. This comprehension allows for the identification of significant influencers and the development of initiatives that leverage social capital to attain widespread adoption. In summary, diffusion models are essential tools for navigating the complex landscape of innovation acceptance in the agricultural industry. Their importance lies in their ability to categorize adopters, take into account social factors, assess perceived qualities, guide interventions through stages, adjust to specific conditions, and combine both social and individual dynamics. Through the utilization of these models, stakeholders in the agricultural industry can construct targeted strategies that promote the implementation of advancements in a manner that is environmentally responsible, hence leading to enhanced productivity, adaptability, and overall progress in agriculture (Neilson, 2001).

Chapter 4 Investigating the Factors Influencing Precision Agriculture Technology Adoption in Italy: A Scoping Review

4.1 Introduction

One of the primary obstacles for sustainable agriculture is to attain maximum output and enhance farm revenue with minimal resource and financial inputs, all while safeguarding the environment. Precision farming (PF) technologies can be utilized to tackle this difficulty. Precision agriculture (also referred to as PF, site-specific crop management, or prescription farming) is a farming management approach that has been evolving since the 1990s. It involves the careful observation, measurement, and response to variations within and between fields in order to achieve maximum profitability, sustainability, and environmental protection. The adoption of Precision Farming (PF) has been made feasible due to advancements in various technologies, including geographic information systems, global navigation satellite systems (GNSS), remote sensing (RS), satellite imagery, ground sensors, as well as components from mobile computing and telecommunication. These technologies, in conjunction with methods to correlate mapped variables with suitable agricultural practices such as tillage, seeding, fertilization, herbicide and pesticide application, irrigation, harvesting, and animal husbandry, have facilitated the implementation of PF. By utilizing in-field or remote sensing measures, it is possible to apply optimal amounts of fertilizers and irrigation water at varying rates. This approach effectively minimizes the environmental consequences of agriculture while also reducing input expenses (Balafoutis et al., 2017).

Although PF has several advantageous characteristics, its utilization among European farmers remains limited (Reichardt et al., 2009; Kutter et al., 2011; Zarco-Tejada, Hubbard and Loudjani, 2014). The limited uptake of Precision Farming (PF) technologies in Europe can be attributed to several factors, including farmers' insufficient awareness, inadequate financial resources to make the initial investments, and the economic infeasibility of such investments due to small land sizes or equipment incompatibility (Zarco-Tejada, Hubbard, & Loudjani, 2014; OECD, 2016). The existing literature on the factors influencing the adoption of PF technologies heavily relies on empirical evidence primarily from the United States. Notable studies include those conducted by Khanna, Epough, and Hornbaker (1999), Khanna and Zilberman (1997), McBride and Daberkow (2003), Paxton et al. (2011), Pierpaoli et al. (2013), Schimmelpfennig and Ebel (2011), Schimmelpfenning (2016/2018), Watcharaanantapong et al. (2014), and Ofori, Griffin, and Yeager (2020). Although there are a limited number of empirical studies conducted in Europe, primarily in Germany and Denmark (Reichardt and Jürgens, 2009; Reichardt et al., 2009; Kutter et al., 2011; Tamirat, Pedersen and Lind, 2018; Pedersen et al., 2006), as well as in the Netherlands, France, Switzerland, Italy (Long, Blok and Coninx, 2016), and Hungary (Lencsés, Takács and Takács-György, 2014), these studies are often qualitative in nature and based on small sample sizes. Additionally, they tend to focus specifically on early adopters of the technology (Kernecker et al., 2020).

Building upon the previous studies, this study seeks to examine the factors that motivate farmers to adopt PFTs, as defined by Adinolfi et al. and Vecchio et al., and identify the obstacles that hinder the adoption process.

4.2 Materials and Methods

This study is a scoping review of the literature, conducted to investigate and synthesize scientific studies on the factors influencing precision agriculture in Italy. This work has utilized the scoping review approach, adhering to the parameters outlined by (Tricco et al., 2018) in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for scoping reviews (PRISMA-ScR). A scoping review is a method of knowledge synthesis that methodically explores, chooses, and combines existing knowledge to identify the fundamental concepts, types of evidence, and research deficiencies in a certain topic or field (Colquhoun et al., 2014). The scoping review technique offers the benefit of consolidating current knowledge with the goal of formulating policy or practice recommendations, while also offering practical directions for future study (Arksey and O'Malley, 2005; Piñeiro et al., 2020). The scoping technique, in contrast to the traditional literature review, strives to be meticulous, transparent, and capable of being replicated. It involves specific measures to minimize the influence of the author's pre-existing knowledge and experience, hence reducing subjectivity bias (Munn et al., 2018).

Following the formulation of the research question, the succeeding stages of this approach include: identification of pertinent studies, selection of studies, extraction and organization of data, and presentation of the findings. To obtain a representative sample of the literature, a preliminary selection of papers has been made. The Scopus and Web of Science bibliographic databases were utilized to conduct a comprehensive search for pertinent studies. This search included publications authored in English and published in peer-reviewed journals between 2011 and March 3, 2022. By doing a comprehensive analysis of the literature, we were able to find these keywords. The following table displays the keywords utilized for this search:

4.2.1 Keywords

Table 4.1 Keywords used for Scoping Review

First set	Precision Agriculture; Precision Viticulture; Remote Sensing; Imagery; Smart Farming; Farm management information system; Decision support system; Site-specific adaptation; Guidance system; Drone; Autosteer sy (Placeholder1)stem Smartphone Sustainable agriculture Precision

	farming Climate-smart agriculture Yield monitoring Georeferenced Soil Mapping Variable-rate application Embodied-knowledge technology Information-intensive technology
Second set	Drivers, Determinants, Factors, Enablers, Motivations, Technology adoption, social network, Diffusion of innovation Use Uptake Implementation
Third set	Choice experiment, Cost-benefit analysis, Enterprise resource planning, Profitability, Case study research

Reverse citation searches were also conducted. Such a combination of databases and search strategies ensures adequate and efficient coverage (Bramer et al., 2017).

4.2.2 Selection criteria

The studies were required to satisfy specific inclusion and exclusion criteria for selection. (1) Only studies that were conducted in English were included. (2) The papers focused on agricultural innovation, specifically the adoption of PA technologies in Italy. (3) The publications covered the disciplines of Agricultural and biological sciences, environmental science, earth and planetary sciences, social sciences, computer science, business, management, and accounting, economics, econometrics, and finance, decision science, and multidisciplinary (4). The publications were considered eligible if they were scholarly pieces published in journals, review articles, books, book chapters, conference papers, or conference reviews.

The exclusion criteria encompassed non-responsive articles that did not meet the inclusion criteria, specifically those published prior to 2011 or after 03 March 2022. Additionally, studies published in languages other than English, articles unrelated to the topic, documents other than journal research articles, review articles, books, book chapters, conference papers, conference reviews, and duplicate studies were also excluded.

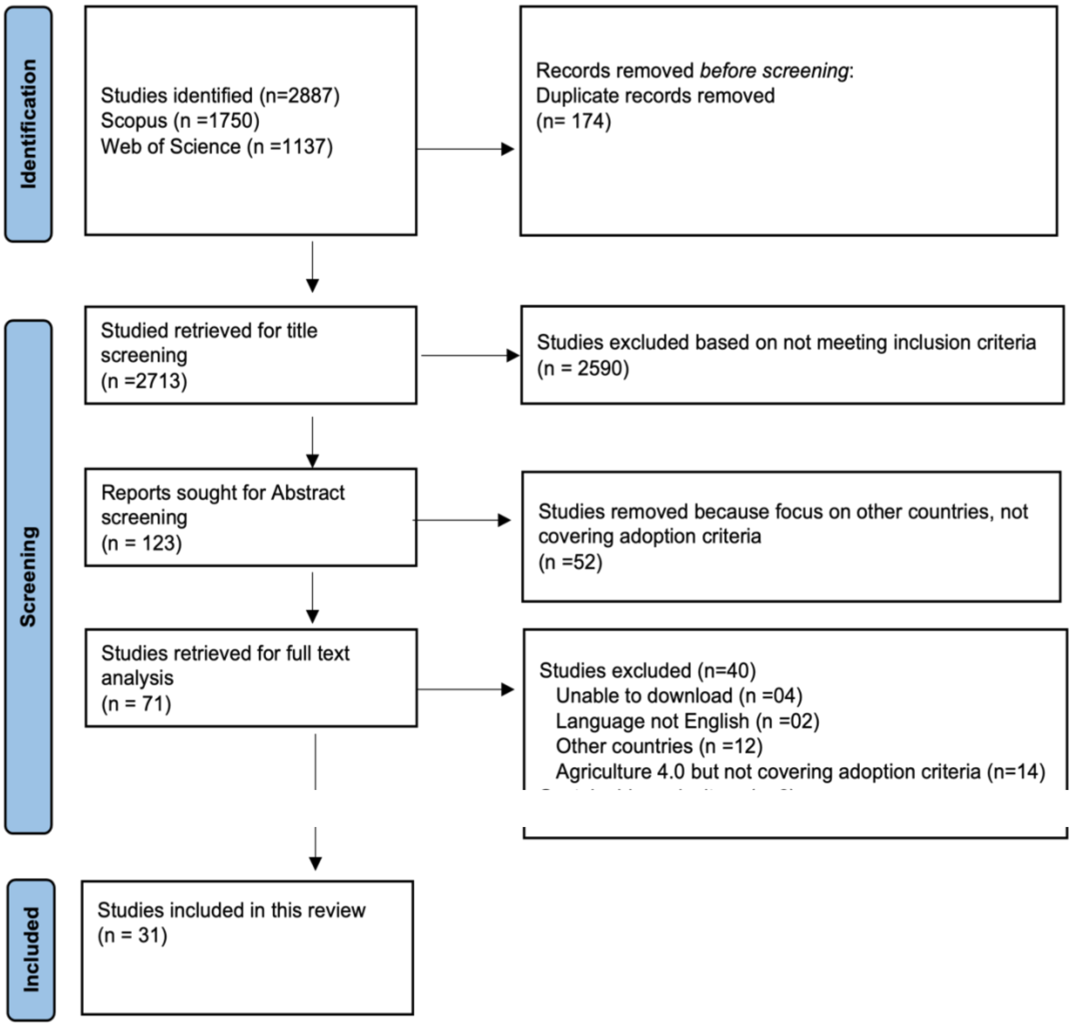

Figure 4.1PRISMA-ScR Flow Diagram

4.3 Results and discussion

A preliminary bibliographic search using the above keywords in the two databases (Scopus and Web of Sciences) yielded a total of 2887 results/publications (1750 from Scopus and 1137 from WOS). Following the elimination of duplicates (174) in Endnote 20, a total of 2713 items were transferred for title screening. Next, the eligibility of the papers was assessed by examining the titles and summaries to determine if they align with the purpose of this study. 2590 articles unrelated to determining the factors influencing the adoption of precision farming technologies were excluded in this step. Subsequently, a total of 123 papers were evaluated based on their abstracts, leading to the elimination of 52 articles due to their lack of relevance. After conducting a thorough investigation of the complete text of the remaining 71 papers, it was found that only 31 of them met the criteria for this scoping review. The other 40 publications did not meet the necessary requirements and were therefore excluded.

The ultimate sample comprises 31 papers composed in English and published in publications written in the English language. Approximately 35% of the articles were published in the year 2020, while 20% were released in 2021. Additionally, 16% were published in 2019, and 13% were published up until the period of the study in 2022. This indicates a recent surge of activity in this domain.

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Table 4.2 General Information on Selected Articles

AUTHOR	Title	Year	Objectives	Area Covered	Models
(Balafoutis et al., 2020)	Smart farming technology trends: Economic and environmental effects, labor impact, and adoption readiness	2020			
(Bentivoglio et al., 2021)	A theoretical framework on network's dynamics for precision agriculture technologies adoption	2022	To investigate the role of various networks in the process of precision agriculture technologies	Different regions of Italy	Conventional content analysis implies a direct approach in which those

			adoption in the agricultural sector		coding categories are derived directly from the text data.
(Blasch et al., 2022)	Farmer preferences for adopting precision farming technologies: a case study from Italy	2022	investigate the determinants of the uptake of PF technologies, 2) explore whether the social influence and the tendency to innovate change the valuation of specific features of the technologies.	Central Italy,	choice experiment, multinomial logit, mixed logit and latent class logit models.
(Giorgia Bucci et al., 2019)	Factors affecting ict adoption in agriculture: A case study in italy	2019	(I) to give an overview of the state of art of PA; (II) to summarize which factors more affect the adoption of PATs, objective of this study is to investigate the relationship between computerization of Italian farms and its determinants through a multiple linear regression in Italy (III) to understand the	Italy	multiple linear regression method

			determinants of technological innovation through a Regression model.		
(G Bucci et al., 2019)	Exploring the impact of innovation adoption in agriculture: How and where Precision Agriculture Technologies can be suitable for the Italian farm system?	2019	to review the factors more affect the adoption of precision agriculture technologies (PATs); secondly, to investigate where the PATs could be convenient to apply in Italy.	Italy	
(Bucci et al., 2020)	Measuring a farm's profitability after adopting precision agriculture technologies: A case study from Italy	2020		Italy	
(Caffaro & Cavallo, 2019)	The effects of individual variables, farming system characteristics and perceived barriers on actual use of smart farming technologies: Evidence from the piedmont region, northwestern Italy	2019	investigating the role played by sociodemographic variables (education), farming system characteristics (farm size and being a sole farmer), and subjective factors (farmers' perceived barriers) in affecting the use of SFTs in a sample of	Piedmont Region, italy	SEM, discrete choice (logit or probit) models

			Piedmontese farmers.		
(Caffaro et al., 2020)	Drivers of farmers' intention to adopt technological innovations in Italy: The role of information sources, perceived usefulness, and perceived ease of use	2020		Piedmont region, Northwest Italy.	Technology acceptance model, Structural Equation modelling
(Caffaro et al., 2019)	An ergonomic approach to sustainable development: The role of information environment and social-psychological variables in the adoption of agri-environmental innovations	2019			
(Cisternas et al., 2020)	Systematic literature review of implementations of precision agriculture	2020	SLR		
(Finco et al., 2021)	The economic results of investing in precision agriculture in durum wheat production: A case study in central Italy	2021			
(Garini et al., 2017)	Drivers of adoption of agroecological practices for winegrowers and influence from policies in the province of Trento, Italy	2017			
(Giua et al., 2021)	Management information system adoption at the	2021	a comprehensive review of contributions from	SLR	

	farm level: evidence from the literature		the scientific literature dealing with the adoption of farm-level digital innovations, with a specific focus on management information system (MIS) technologies, defined as a set of software systems used to support human decision-making within farm management activities		
(Giua et al., 2022)	Smart farming technologies adoption: Which factors play a role in the digital transition?	2022			
(Long et al., 2016)	Barriers to the adoption and diffusion of technological innovations for climate-smart agriculture in Europe: evidence from the Netherlands, France, Switzerland and Italy	2016	frontiers (Greene, 2010) with a metafrontier production function approach (Huang et al., 2014).		
(Merloni et al., 2018)	Adaptive capacity to climate change in the wine industry: A Bayesian Network approach	2018			
(Miao & Khanna, 2020)	Harnessing advances in agricultural technologies to optimize resource	2020			

	utilization in the food-energy-water nexus				
(Monteleone et al., 2020)	Exploring the Adoption of Precision Agriculture for Irrigation in the Context of Agriculture 4.0: The Key Role of Internet of Things	2020			
(Ofori & El-Gayar, 2021)	Drivers and challenges of precision agriculture: a social media perspective	2021			
(Pagliacci et al., 2020)	Drivers of farmers' adoption and continuation of climate-smart agricultural practices. A study from northeastern Italy	2020			
(Pathak et al., 2019)	A systematic literature review of the factors affecting the precision agriculture adoption process	2019			
(Pierpaoli et al., 2013)	Drivers of Precision Agriculture Technologies Adoption: A Literature Review	2013	to evaluate the drivers of PA adoption by combining and comparing ex-post and ex-ante studies to elucidate possible relations between the two		
(Sarri et al., 2020)	Smart farming introduction in wine farms: A systematic review and a new proposal	2020			

(Shang et al., 2021)	Adoption and diffusion of digital farming technologies-integrating farm-level evidence and system interaction	2021			
(Sood et al., 2022)	Artificial intelligence research in agriculture: a review	2021			
(Tey & Brindal, 2022)	A meta-analysis of factors driving the adoption of precision agriculture	2021			
(Tey & Brindal, 2012)	Factors influencing the adoption of precision agricultural technologies: A review for policy implications	2012			
(Vecchio, De Rosa, et al., 2020)	Adoption of precision farming tools: A context-related analysis	2020	to look into the relevant dimensions of context affecting the uptake of Precision farming Techniques		
(Vecchio, Agnusdei, et al., 2020)	Adoption of precision farming tools: The case of italian farmers	2020			
(Vecchio et al., 2022)	The leading role of perception: the FACOPA model to comprehend innovation adoption	2022			
(Yatribi, 2020)	Factors Affecting Precision Agriculture Adoption: A Systematic Litterature Review	2020	to conduct a review of the systemic literature with the aim of identifying the main factors for the adoption of PA	Global	

			technologies on a global scale.		

4.3.2 Factors Influencing the Adoption of Innovative Agriculture Technologies

The literature analysis identified 21 characteristics that may impact the adoption of PA systems. To provide a comprehensive overview of the study conducted, present a summary of all the selected papers in the table above(Table 4.2). The variables were further categorized into four sets of explanatory variables: individual factors, organizational factors, environmental factors, and technology aspects. Consequently, the researchers discovered a total of 10 distinct components, which accounted for around 48% of all factors. These factors were most frequently detected by the researchers. There are four organizational and institutional elements, each accounting for 19% of all the identified factors. Ultimately, the characteristics pertaining to the technology itself are recognized as decisive elements in the process of adoption, specifically, three factors have been identified.
Subsequently, we can categorize these factors based on their level of significance and impact on the acceptance of new physical activity technologies. The table below presents the ranking of criteria, indicating the frequency with which they were identified in the 41 publications reviewed as determinants for the adoption of PA technology.

An examination of the 31 carefully selected publications in the literature uncovered several elements that may have an impact on the adoption of PA technology. To provide a comprehensive overview of the research conducted, we present a summary of all the selected papers in the table above (4.2.)
Categorized these variables into four kinds of explanatory variables: individual factors, organizational factors, environmental factors, and technical aspects

4.3.2.1 Individual Factors

Age is found as a factor of adoption in all 31 analyzed articles. Elderly agricultural practitioners often exhibit a conservative mindset and display hesitancy towards embracing new technologies, mostly driven by their aversion to risk (Kaliba et al., 2020). Brown et al. (2019) elucidates that elderly farmers have a higher propensity for risk aversion, a diminished inclination to engage in technological experimentation, and a reduced susceptibility to the advantages offered by novel technology. According to Paustian and Theuvsen (2017), young farmers exhibit a greater willingness to embrace innovations and are more inclined to incorporate new technologies into their practices. According to Reichardt and Jürgens (2009), the adoption of technology by older farmers can be attributed to the significant upfront expenses involved. Unlike younger farmers, older farmers often possess the necessary financial resources to acquire these technologies.Education is regarded as the third most commonly cited element, being mentioned 11 times as a determinant of adoption.The correlation between education level and the adoption of new technologies is highlighted by numerous writers (Bucci et al., 2019; Carrer et al., 2017; Gyata, 2019; Reichardt and Jürgens, 2009).(Kaliba et al., 2020) discovered that the adoption rate of technology among farmers is positively correlated with their level of education, particularly when the technology is advanced. Furthermore, they emphasized the need of learning for effectively utilizing the technology.An individual who engages in farming not only becomes familiar with its application, but also develops a receptiveness to embracing new ideas and methods.

Gender is a significant element in adoption, since it has been recognized as a determining factor six times. Nevertheless, the impact of gender on the adoption of emerging technology remains uncertain. Danso-Abbeam et al. (2019) demonstrate that men exhibit a higher tendency to embrace technology compared to women. However, Hay and Pearce (2014) discover that women hold a more favorable perception than men regarding the advantages of new technologies. This research underscores the enthusiasm of rural women towards technology, which has allowed them to attain significant advantages, such as the adoption of a livestock management system. According to the author, rural women exhibit a threefold increase in the utilization of new technology compared to men.

As previously stated, the literature has established a strong correlation between the cost of acquisition and both agricultural and non-agricultural revenue (identified six times). Studies indicate a positive correlation between farm profitability and the likelihood of farmers adopting new technologies (Miller et al., 2019). The presence of nonfarm income also enhances the likelihood of adoption (Ng'ang'a et al., 2019). Barnes et al. (2019) elucidates that off-farm income serves as a source of cash for farmers with moderate income, enabling them to procure innovative technology. The ability to engage in income-generating activities outside of farming is typically linked to the introduction of technology. According to Griffin et al. (2017), the act of adopting something comes with significant initial expenses, and farmers with higher incomes are more inclined to adopt it. Lambert et al. (2015) demonstrated that a 10% rise in farming revenue corresponded to a 9.2% rise in the likelihood of producers adopting these technologies. The ranking is led by perceived utility, which has been cited twenty-one times as a key factor in adoption. Farmers seem to be more inclined to embrace novel technologies once they have observed its practicality in real-world agricultural settings (Barnes et al., 2019; Brown & Roper, 2017; D'Antoni et al., 2012; Dela Rue & Eastwood, 2017; Griffin et al., 2017; Mengistu & Assefa, 2019, 2019; Ng'ang'a et al., 2019). For instance, Brown and Roper (2017) conducted a study on technology adoption in the Italian dairy sector. They found that farmers are mostly influenced to accept new technologies through demonstrations within farmer networks, which then encourages them to adopt the same technology (Brown and Roper, 2017). Zhang et al. (2019) assert that the adoption of cleaner production techniques (CPT) by farmers depends not only on their perception of its utility, but also on their observation of other farmers who have previously embraced this technology and are satisfied with it.

Conversely, some authors argue that the farmer's experience serves as a measure of their proficiency in the field of agriculture (Brown et al., 2019; Carrer et al., 2017; Griffin et al., 2017; Paustian and Theuvsen, 2017). The role of experience is recognized as a determining element in adoption, however, the research findings do not yield consistent conclusions. Paustian and Theuvsen (2017) demonstrated that those with less than 5 years of experience, as well as those with 16 to 20 years of experience in agriculture, are more likely to embrace new technologies. Conversely, Carrer et al. (2017) discovered that farmers with extensive expertise tend to resist the adoption of information systems.

An examination of the existing research highlights an additional significant element that influences the acceptance of novel technology, specifically the disposition towards risk. Certain farmers have a preference for utilizing the resources available to them rather than making investments in novel technologies (Miller et al., 2019). This hesitancy can be attributed mostly to the ambiguity around the utilization of technology, as well as the uncertainty regarding the economic benefits. When the market price of agricultural products decreases, farmers typically reduce their investments in capital, such as machinery and innovation. For instance, Barnes et al. (2019) highlight that farmers with reduced ambiguity on the economic benefits of VRNT are more inclined to allocate resources towards adopting these technologies. Advanced technologies necessitate supplementary expenditure in acquiring knowledge. According to Ng'ang'a and colleagues (2019), a lack of skills and knowledge has a detrimental impact on the adoption process.

The findings indicate that technologies which necessitate specialized expertise and technical knowledge are less likely to be adopted. Danso-Abbeam et al. (2019) discover that the size of a home is a determining factor in both the likelihood and degree of adoption. This can be linked to the accessibility of domestic labor.

Individuals who belong to a group or organization. In their study, Kaliba et al. (2020) emphasize the significance of labor availability in the process of technology adoption, particularly in situations when there is a shortage of labor and recruiting extra workers is challenging. Alternatively, if there is an abundant and inexpensive work supply, or if the likelihood of household members securing non-farm jobs is diminished, the adoption of labor-intensive technology is probable. Ng'ang'a et al. (2019) found that there is a negative correlation between labor costs and the probability of choosing labor-intensive farming methods.

4.3.2.2 Organizational factors

The size of the farm is the second most frequently reported factor influencing adoption, with a frequency of 11 times. Carrer et al. (2017) elucidates that the management of large farms is more intricate, and recent advancements in technology have demonstrated their efficacy in enhancing production efficiency and diminishing expenses. Danso-Abbeam et al. (2019) elucidate that there exists a correlation between farm size and the adoption of novel technologies, as farmers with larger farms are more inclined to allocate a portion of their land for initial experimentation with new technologies, unlike smaller farms. The findings are consistent with other findings from prior research on the use of precision agriculture technology (Brown et al., 2019; Carrer et al., 2017; Paustian and Theuvsen, 2017; Reichardt and Jürgens, 2009; Welsh et al., 2010).The expense associated with obtaining technology is frequently recognized as a key factor influencing its adoption (reported in 9 instances) (Carrer et al., 2017; Chang and Tsai, 2015; Keskin and Sekerli, 2016; Khanal et al., 2019).Gyata (2019) and Reichardt and Jürgens (2009) highlight that most farmers exhibit hesitance in adopting precision farming techniques mostly due to their exorbitant expenses.Large farms are more inclined to embrace precision farming technologies compared to small farms due to their greater financial resources (Barnes et al., 2019).However, the literature has closely associated the cost of acquisition with both agricultural and non-agricultural income.However, Barnes et al. (2019) argue that the absence of reduced land tenure would hinder farmers' adoption of the technology.Undoubtedly, farmers who own title deeds are more inclined to engage in soil-enhancing techniques compared to those who do not possess title deeds.The findings align with those of Barnes et al. (2019), suggesting that land titles grant farmers the authority to utilize the land.Various studies (Lambert et al., 2015; S.ogo and Zahonogo, 2019; Welsh et al., 2010) have shown that farmers who possess property certificates experience increased feelings of security, enabling them to engage in long-term investments.The non-adoption of drip irrigation is typically attributed to the location's lack of eligibility for subsidies.Conversely, certain studies have indicated that farmers engaged in commercial farming are more inclined to adopt innovations, as they actively want to enhance their productivity, in contrast to subsistence farmers.The study conducted by Barnes et al. (2019) reveals that the utilization of these technologies leads to a 10% improvement in outcomes for commercial farmers, while resulting in a 26% decline for subsistence farmers.The author posits that this phenomenon may also be attributed to the propensity of commercial farmers to take risks, as opposed to non-commercial farmers.Lambert et al. (2015) demonstrated that the adoption process is a dynamic and intricate phenomenon associated with alterations in land use.For instance, the presence of cattle has a beneficial impact on the adoption of new technologies.Furthermore, Lambert et al. (2015) shown that the date of adoption is influenced by elements that are associated with the characteristics of the far.Adnan et al. (2017) and Mengistu and Assefa (2019) have demonstrated that the variable "crops grown" has a significant impact.Many farmers contend that drip irrigation is unsuitable for mature plantations due to its alleged inability to adequately fulfill the water needs of trees with well-established deep root systems.Market gardeners that work in greenhouses often specialize in drip irrigation.

4.3.2.3 Institutional Factors

The majority of research highlight the significance of public service intervention in regards to the adoption of new technology. Studies have demonstrated that awareness, access to agricultural extension services, credit facilities, and the practice of aggregation are crucial factors in promoting the adoption of technological innovations (Adnan et al., 2017; Mengistu and Assefa, 2019; Mengistu, 2019; Barnes et al., 2019; Danso-Abbeam et al., 2019; Gyata, 2019; Kaarthikeyan and Suresh, 2019).

In their study, Mengistu and Assefa (2019) discovered that training and extension programs are effective in increasing awareness and facilitating the implementation of watershed management methods. Reichardt and Jürgens (2009) highlight the significance of a high-quality advising service and the provision of essential information.The author highlights the obstacles of insufficient counseling and training in the adoption process, emphasizing that the mere presence of the internet is not a satisfactory determinant for farmers.The availability of credit services for farmers is recognized as a factor that influences the level of adoption, as access to bank credit enables farmers to get additional financial resources, which in turn enables them to invest in new technology.Multiple research (Danso-Abbeam et al., 2019; Gyata, 2019; Kaarthikeyan and Suresh, 2019) have found that farmers' utilization of loan services positively correlates with the adoption of technological advancements. Barnes et al. (2019) have demonstrated that subsidies and taxation are regarded as favorable catalysts for the adoption of novel technologies. According to Adnan et al. (2017), the use of green fertilizers is closely associated with specific financial measures, such as capital grants for upkeep, tax reductions for adopters, lower interest rates, and technical assistance to promote the adoption of green fertilizers. These measures aim to lower costs and ultimately enhance crop yields. Kaarthikeyan demonstrates a substantial correlation between the variable "amount of subsidy" and the adoption rate. Specifically, a higher amount of subsidy is associated with a greater probability of adoption. The variable difficulty in receiving the subsidy is logically associated with a comparatively low rate of adoption. As the accessibility of the subsidy decreases for farmers, the likelihood of their adopting drip irrigation decreases.

4.3.2.4 Technological Factors

The adoption of PA technologies is strongly influenced by the perceived ease of use, which has been identified as a significant factor on ten occasions. According to Adnan et al. (2017), the adoption of Agricultural Management Practices (AMPs) by farmers is influenced by their perception of how easy it is to use, their personal standards, and their perception of their ability to manage their behavior. The analysis indicates that farmers' impression of the usability of PA technology has a substantial influence on its adoption. If a farmer finds PA technology to be intricate or challenging to utilize, they are consequently less like to embrace it (Aubert et al., 2012).

Conversely, the matter of technology compatibility frequently emerged during the examination of perceived usefulness. Aubert et al. (2012) highlight the significance of technological compatibility, demonstrating that it has the most significant impact on the perceived usefulness of the technology and a very influential effect on its ease of use. The absence of compatibility can generate ambiguity and hesitancy among farmers to invest significant capital expenditures in PA technology (Higgins et al., 2017). Thus, aligning standards with farmers' practices would optimize compatibility, leading to enhanced perceived utility and ease of use, ultimately resulting in increased adoption (Aubert et al., 2012). According to Nordin et al. (2014), the adoption process is influenced by various factors, including the quality of the information offered by the technology.

4.4 Conclusion

The objective of this contribution was to consolidate the past decade's literature on the implementation of precision farming technologies. For this systematic review, a total of 31 papers were chosen using the prisma statement approach, which stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses. A comprehensive investigation was undertaken to ascertain all the elements that influence the adoption of technology by farmers.

The findings of this evaluation, along with the constraints and outlooks of the investigation, can be succinctly summarized as follows: The results indicate that individual variables are mostly recognized as determinants of the adoption of precision farming technologies. Consequently, the farmer holds a pivotal role in determining whether to adopt or not. However, perceived utility continues to be the primary element identified in this scoping review as a determining factor for adoption. Therefore, based on the acquired results, there is no consensus on the influence of various parameters on adoption. The farmer's gender and experience do not always serve as decisive factors. Further efforts are required at this stage. Adoption factors were typically analyzed as distinct variables in the majority of research. The analysis of the results demonstrates clear correlations between the elements, such as a close association between income and the cost of obtaining technology. This implies that in future research, it would be more appropriate to consider these elements as covariates or moderating variables. However, this study has many limitations. It is probable that there are unpublished works and research conducted in languages other than English that were not taken into account and incorporated in this study. Considering that English is the primary language for sharing research globally, and acknowledging the challenges of accessing unpublished documents, these limitations are unlikely to significantly impact the obtained results. However, because to the heterogeneity of the research included, it is not possible to make comparisons, do meta-analyses, or draw recommendations for future applications. This suggests that additional investigation is required in this particular domain. The literature on determinants seems to be predominantly from English-speaking countries, which introduces a selection bias. At this level, one may question if the factors influencing adoption would vary based on the level of development in different countries. It is plausible to infer that farmers in a developed nation are mostly impacted by individual variables rather than institutional considerations. For instance, in underdeveloped nations, when there are obstacles within the system (such as bureaucratic procedures for drone usage, insufficient financial backing, and lack of guidance), these challenges are more prevalent. One may argue that the level of innovation is more advanced in certain countries compared to others. At this stage, an intriguing study path involves assessing the level of innovative thinking among farmers and its impact on their willingness to adopt new agricultural technologies. Based on the findings of this research, there has been a lack of investigation on this particular issue. In the end, our work can serve as the foundation for additional empirical research on the factors that influence adoption. Additionally, it can assist public authorities in establishing a program to modernize the agriculture industry. Digitization is becoming a must in all areas of the economy, including agriculture.

Chapter 5 Theoretical Framework: Precision agriculture technology adoption and technical efficiency

5.1 Impact of precision agriculture technology on technical efficiency

Precision agriculture technology is a game-changing approach to modern farming that makes use of advanced technologies to improve performance in terms of efficiency, sustainability, and productivity. Precision agriculture (PA) uses inter- and intra-field variation in soil, topography and climate to optimize input application and increase profitability. PA promises to enhance efficiency by spatially targeting inputs to where they are most productive, thereby maximizing overall output for a given mix of resources. Technologies such as automated guidance systems, variable rate technology (VRT), and yield mapping have grown in popularity since their introduction in the 1990s, and newer technologies, including unmanned aerial vehicles (UAVs) and multi-spectral sensors, are being adopted more widely now (Lezoche et al., 2020).

Of particular interest is the ability of adopters of different PA technology bundles to improve efficiency. The use of information technology and a variety of tools, including but not limited to GPS guidance, control systems, sensors, robots, drones, autonomous vehicles, variable rate technologies, GPS-based soil sampling, and automated hardware, are all components of precision agriculture, which is also sometimes referred to as precision farming. Due to the availability of these technologies, farmers are able to improve their resource management and make decisions that are better informed and adapted to the specific conditions of their fields. One of the most important aspects of precision agriculture is the application of technology that utilizes the Global Positioning System (GPS). Devices that are equipped with GPS, such as tractors and drones, are able to offer precise location information, which enables farmers to precisely map and monitor their fields. The use of global positioning system (GPS) technology makes a substantial contribution to the spatial management of agricultural resources, as stated by (Fountas et al., 2005).

A network of sensors is used in precision agriculture to collect data in real time on a variety of characteristics, including the amount of moisture in the soil, the amount of nutrients present, and the overall health of the crop. According to (Fountas et al., 2005; Sankaran et al., 2015), these sensors make it easier for farmers to make decisions based on data by providing them with precise information about the conditions that exist in various regions of their fields. Having access to such real-time data is beneficial for optimizing techniques for pest management, fertilization, and watering.

Variable rate technology, often known as VRT, is an additional essential component of precision agriculture. The use of variable rate technology (VRT) makes it possible to apply inputs like fertilizers and pesticides at different rates over a field. These rates are determined by the precise requirements that are determined through data analytics. According to Lambert et al. (2017), this focused approach contributes to the general improvement of resource utilization efficiency as well as the reduction of input waste.

Drones, also known as Unmanned Aerial Vehicles (UAVs), have become increasingly popular in the field of precision agriculture due to their capacity to take high-resolution imagery of agricultural fields. Monitoring crop health, identifying insect infestations, and evaluating the general conditions of the field are all made easier with the assistance of these aerial platforms. As stated by Anderson and Gaston (2013), unmanned aerial vehicles (UAVs) provide a method of data collecting that is both efficient and cost-effective for applications related to precision agriculture. Additionally, robotics and autonomous vehicles have made their way into the realm of precision agriculture. As a result of the use of automated tractors and robotic systems, field operations may be performed with greater precision and control, hence minimizing the need for human intervention.

There is a significant amount of value in the application of precision agriculture technologies. Precision agriculture (PA) assists in the promotion of sustainable agricultural methods by maximizing the utilization of resources and limiting the impact on the environment. According to Srinivasan et al. (2017), increased efficiency in resource management, which is made possible by precision agriculture, translates to cost savings for farmers. Furthermore, according to (Fountas et al., 2005) precision agriculture helps to improve overall crop yields and quality by implementing focused treatments that are based on correct data. In conclusion, the technology of precision agriculture, which includes global positioning system (GPS), sensors, variable rate technology (VRT), drones, and robotics, is a revolutionary approach to modern farming. Through the integration of these technologies, farmers are able to make decisions based on data, maximize the utilization of resources, and improve farm management throughout the entire operation. The future of agriculture around the world is being shaped by precision agriculture, which offers a variety of benefits, including better sustainability, improved efficiency, and increased profitability (Erickson & Fausti, 2021; Kernecker et al., 2020)

Despite the promise of PA technology, its impact on efficiency is not well understood. Therefore, the present chapter reviews the literature on the theory related to the production function in agricultural economics, and methods to measure technical efficiency. It is needed since estimating the production function is the prerequisite to evaluating the performance of farms.

5.2 The Production Function in Agricultural Economics

Farmers are economic agents who continuously have to decide how much input to devote to the growth of crops and animals. While exerting their everyday actions, farmers face decisions concerning how much land, capital, labour, and other inputs to allocate in the production processes. Within a system-orientated approach to the company, the production process is commonly described as a transformation of inputs into outputs, as shown in Figure . It is also affected by non-controllable exogenous variables and managerial skills, which play a highly relevant role.

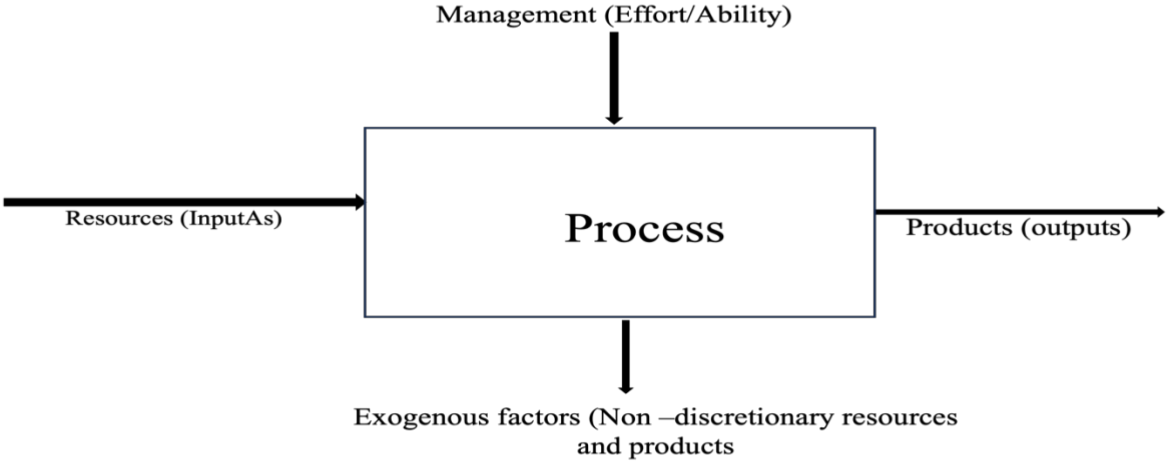

Figure 5.1 System-orientated approach to the firm (Bogetoft & Otto, 2010).

In economic literature, the production process is depicted by the production function, which represents the quantity of output that may be generated based on a specific production method and different amounts of input. The production function is a mathematical representation of how inputs are transformed into outputs. It shows the greatest output that can be achieved from a specific combination of input numbers, assuming that the technology is utilized to its fullest extent (Kumbhakar & Lovell, 2003). The production function usually is expressed with a mathematical representation of the technology, such as:

$$y = f(x_1, x_2, \ldots . x_k) = f\,(x) \qquad (1)$$

where the function f (·) indicates the production technology which transforms a vector of inputs (x) into output (y). For example, a production function that refers to a production process that employs two inputs (x_1 and x2) to produce a single output (y) can be shown as illustrated in Figure 5. In this case, the production function represents the maximum output y obtainable from the varying combinations of the inputs x_1 and x_2. The surface of the curve and the underlying area define the production possibilities set, which contains all the feasible input-output combinations given the production technology.

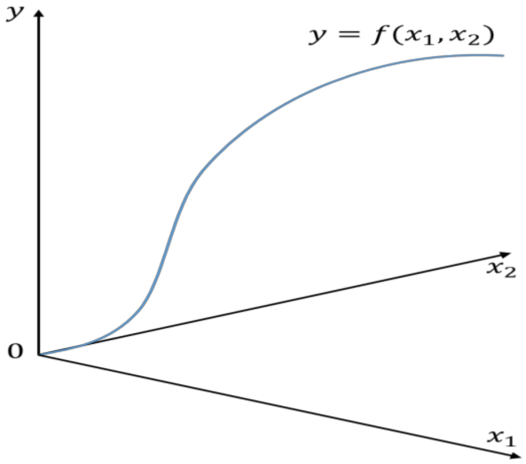

Figure 5.2 Production function example with two inputs and one output (Own elaboration)

Nevertheless, because to the complexity of interpreting the impact of inputs in a multi-dimensional context, researchers typically focus on the two-dimensional aspect, which illustrates the relationship between a single input and a single output. The production function can be analyzed by isolating a specific value of x_2. This allows us to observe the relationship between the input level of x_1 and the output y, which is commonly known as the total product curve of x_1. This relationship is visually represented in Figure 6. By employing a specular approach, one can derive the complete product curve of x_2 for a specific value of x_1.

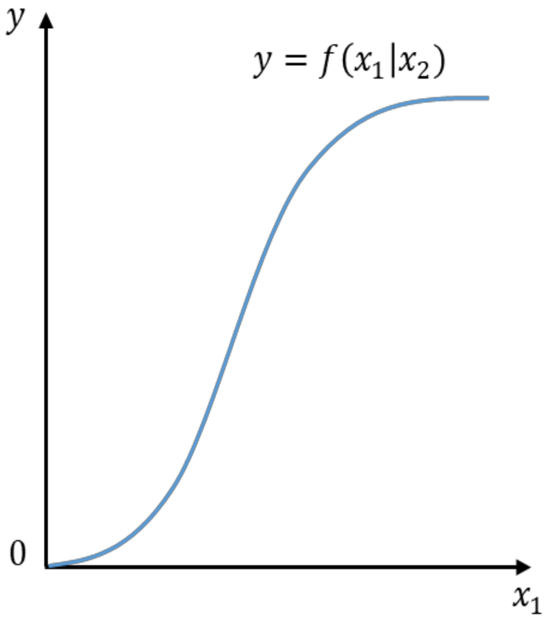

Figure 5.3 The total product curve of x1

The production function is assumed to satisfy some properties to approximate the economic behaviour of economic agents, such as: (I) δy / δxi > 0 implies that the additional use of input increases (or at least does not decrease) the level of output; (II) δ2y / δ2xi < 0 refers to the law of diminishing returns or law of diminishing marginal productivity and implies that the quantity of additional output obtained from the supplemental level of input applied become smaller with the increasing value of input usage. More technical details for all the assumptions related to the production function are provided in (Chambers et al., 1998).

As indicated by (Ellis, 1993) first, in agricultural production, it is possible to find a situation where output occurs in the complete absence of some inputs. For instance, it can be generated output without applying some producing inputs such as fertilizer, irrigation, and pesticide. It implies that the production function may not start from the origin of the axis for some factors. Second, increasing the amount of some inputs such as fertilizer, pesticide, and water increases output, but only up to a certain point. Beyond that threshold, for example, an imbalance between the fertilizer and other plant nutrients in the soil arises, eventually causing output declines when more fertilizer is applied. Therefore, agricultural economics researchers worked to relax some of the properties discussed by Chambers (1998) to estimate the production function in agricultural economics.

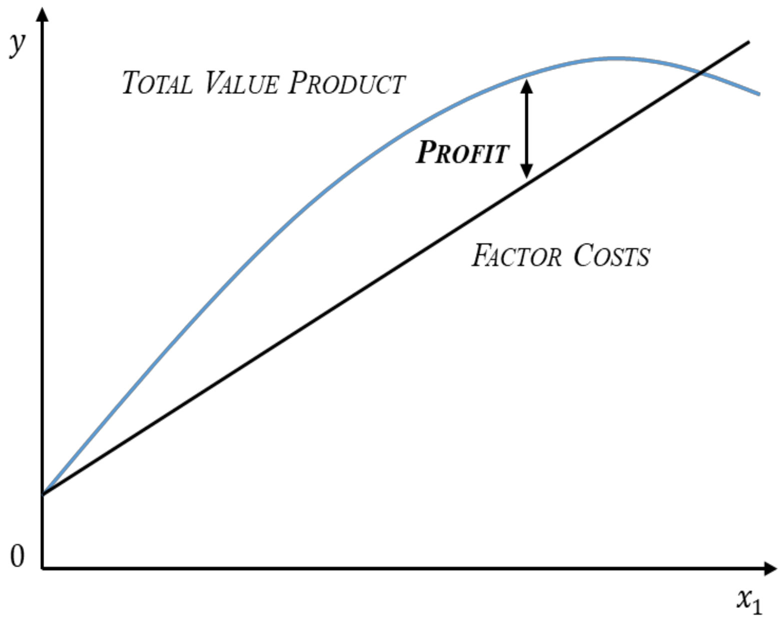

Figure 5.4 The production function for some of the agricultural inputs

Source: Own elaboration based on Ellis (1993)

As for the functional forms of production functions, the most used in the literature are Cobb-Douglas and translog. The translog production function has several desirable properties that make it particularly interesting for this study. The main advantage of adopting a translog production function instead of a Cobb-Douglas is that it is more flexible and allows to investigate of whether the inputs are substitutes or complements (Henningsen, 2020).

In the field of agricultural economics, the production function is a way of describing the relationship between inputs (such land, labor, capital, and technology) and outputs (like crop yields or livestock products) in agricultural production. For the purpose of analyzing and optimizing resource allocation for agricultural practices that are both efficient and sustainable, it serves as a vital tool for economists, policymakers, and farmers. It is possible to conduct an analysis of input substitution and the marginal productivity of each input through the utilization of the production function. In order to determine the impact that changes in input quantities and combinations have on the overall output, it is possible to evaluate these changes. In order for farmers to make decisions regarding the distribution of resources in order to improve production efficiency, it is essential for them to have this information.

In the field of agricultural economics, there is a plethora of empirical applications of the production function. For instance, the Cobb-Douglas production function was utilized in a study that was conducted by Bravo-(Bravo-Ureta & Evenson, 1994) in order to investigate the influence that various inputs had on agricultural output in Chile. According to the findings of the study, the variation in agricultural output was greatly influenced by land, labor, and capital.

In a similar manner, Rasmussen and Zilberman (1986) conducted a study in which they utilized the production function to evaluate the significance of the link between the various inputs and output in the agricultural sector of California. The outcomes of their study brought to light the significance of water, land, and labor in determining crop yields. Furthermore, they highlighted the importance of the production function in agricultural regions that are limited in their access to water.

Not only is the production function valuable at the farm level, but it also plays a role in the decision-making process regarding policy. When it comes to the evaluation of agricultural policies, such as subsidies or technical interventions, the production function is a useful instrument for determining the potential impact that these policies could have on the total productivity of agriculture. According to the findings of a study conducted by Huffman (1986), it is vital to have a comprehensive understanding of the production function in order to effectively establish policies that are in line with the objectives of increasing agricultural output and ensuring sustainability.

On top of that, debates on the implementation of agricultural technology should not be separated from the production function. Some examples of technological breakthroughs that influence the production function are genetically modified crops and precision farming. These advancements have an effect on the efficiency with which inputs are turned into outputs. In a study that was conducted by Alene and her colleagues in 2009, the production function was utilized to investigate the influence that enhanced maize varieties had on the overall productivity of farms in Ethiopia (Alene et al., 2009).

In conclusion, the production function is a fundamental component of agricultural economics. It offers a methodical framework for analyzing the connections that exist between the inputs and outputs that are involved in agricultural production. Researchers and policymakers are able to acquire useful insights into the efficiency, sustainability, and prospective changes in agricultural systems through the use of empirical applications and theoretical models.

5.3 Technical Efficiency

In microeconomics, technical efficiency (TE) is the effectiveness with which a given set of inputs (e.g., land, labor, fertilizer and machinery) is used to produce an output (e.g., crop). A technically efficient firm produces the maximum output from a given quantity of inputs and production technology (output-oriented TE). Alternatively, a technically efficient firm uses the minimum quantity of inputs to produce a given quantity of output using the available production technology (input-oriented TE) (Koopmans, 1951).

In the field of economic analysis, technical efficiency is an essential term, particularly in the field of agriculture, where the efficient utilization of resources is of utmost importance in ensuring that farming techniques are both sustainable and productive. The ability of a production system to obtain the highest possible level of output from a specific set of inputs or to create a specific level of output while utilizing the least amount of inputs is what is meant by the term "technical efficiency." To put it another way, it evaluates the efficiency with which a farm or agricultural activity takes advantage of its resources in order to produce outputs.

The importance of technical efficiency in agriculture can be broken down into several different categories. Its significance in optimizing resource utilization is one of the most important implications. The efficient utilization of resources not only maximizes production but also decreases waste, which contributes to the cost-effectiveness and environmental sustainability of the endeavor. According to Kalirajan and Shand (1999), increasing the technical efficiency of agricultural practices can result in a more sustainable utilization of the natural resources available to farmers.

It is also helpful for policymakers to identify areas that require action and support, which is another benefit of technical efficiency study. The use of technical efficiency analysis to dairy farms in Chile was the subject of a study that was conducted by Bravo-Ureta and Pinheiro (1997). The findings brought to light variations in levels of efficiency, which led policymakers to adopt support programs that were tailored to meet specific issues that were encountered by farms with lower levels of efficiency.

There is a strong connection between the concept of technological efficiency and the overarching objectives of expanding agricultural growth and reducing poverty. There is a greater likelihood that efficient farms would yield excess production, which will contribute to an increase in income for farmers and provides communities with better food security. As Zhang, Wang, Karagiannis, and Xin (2009) have demonstrated, increasing the efficiency of technological processes can play a significant role in the accomplishment of these more general societal objectives.

The improvement of technical efficiency becomes an absolute necessity when viewed in the context of global concerns such as the increasing demand for food and the changing climate. (Karagiannis & Sarris, 2005) conducted a study that highlighted the significance of technical efficiency in resolving these difficulties. They underlined the importance of promoting sustainable farming techniques that maximize the utilization of resources and minimize the impact on the environment.

In conclusion, technical efficiency is an essential term in agricultural economics. It offers a quantitative measurement of the degree to which resources are employed in the production process in an efficient manner. Researchers and policymakers are able to acquire useful insights into the factors that influence productivity and the variations in efficiency that exist among farms through the use of approaches such as Data envelopment analysis (DEA). In order for agriculture to develop toward techniques that are more environmentally friendly, cost-effective, and socially impactful, it is necessary to work toward improving its technical efficiency.

5.3.1 Input-Oriented and Output-Oriented Technical Inefficiency

A production plan is considered technically inefficient when a higher level of output is achievable given the inputs (output-oriented measure), or when the observed output level can be produced using fewer inputs (input-oriented measure). Visually, inefficient production plans are positioned below the production frontier, as illustrated in Figure 5.5. In this figure, f(x) represents the production frontier, and point (A) signifies an inefficient production point. There are two perspectives to understand its inefficiency. Firstly, at the current input level (x), more output could be generated, as evidenced by the distance (AB), indicating output loss due to technical inefficiency. This serves as the basis for measuring output-oriented (OO) technical inefficiency. Secondly, point (A) is inefficient because the same output level could be achieved with fewer inputs, represented by the distance (AC). This distance indicates the potential reduction in input without diminishing output and forms the basis for measuring input-oriented (IO) technical inefficiency. It's important to note that estimates of inefficiency depend on the specific technology (production frontier) in use. An input–output combination may appear inefficient under one technology but could be efficient under a different one. Consequently, in empirical analyses comparing the technical inefficiencies of various producers, it's crucial to estimate them in relation to the appropriate technology.

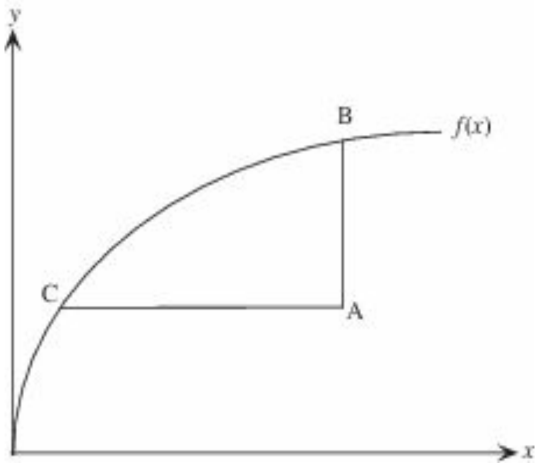

Figure 5.5 IO and OO Technical Inefficiency for the One-Input, One-Output Case

5.3.2 Approaches to Technical Efficiency Measurement

In literature, most productivity and efficiency analyses are conducted through the development of production frontier models. The two commonly used methods in productivity and efficiency analysis are the Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Although these two methods have their merits, there has been constant debate amongst scholars on which method is better for modelling production technology. A relevant distinction between the two methods is that DEA is deterministic while SFA is stochastic. While in the stochastic frontier model the individual observations may be affected by random noise, in the deterministic approach the potential noise is neglected, and each variation in data is assumed to influence the firm's efficiency and the shape of the frontier (Aigner et al., 1977).

Stochastic Frontier Analysis (SFA) is a parametric approach that acknowledges the presence of inefficiency and random noise in production processes. SFA was developed by (Aigner et al., 1977) It does this by producing an estimate of a production frontier that represents the greatest output that is practicable given the inputs, and it takes into account any departures from this frontier as a combination of technical inefficiency and random factors. When there is a requirement to differentiate between visible performance and intrinsic inefficiency, SFA is a technique that is frequently utilized (Battese and Coelli, 1992).

Farrell (1957) first introduced the theoretical basics for measuring productive efficiency. Following that, (Charnes et al., 1978) proposed Data Envelopment Analysis (DEA) which is one of the non-parametric approaches that uses mathematical programming techniques to estimate the technical efficiency of comparable decision-making units (DMUs). Data Envelopment Analysis (DEA) is a method that is extensively used for the purpose of measuring the efficiency of technical processes. A comparison of the input-output ratios of various units, such as farms in the case of agriculture, is used by DEA to determine the relative efficiency of these various units. The efficiency score can range anywhere from 0 to 1, with 1 represent the highest possible level of efficiency. Through the analysis of the input-output ratios of decision-making units (DMUs), it analyzes and contrasts the effectiveness of these units. The DEA is especially helpful in circumstances in which the functional form of the production connection is either unknown or difficult to explain.

The construction of efficiency indices can be accomplished through the use of index numbers and ratios, which are basic ways. These methods entail comparing the actual output levels with the highest attainable output given the input levels. Index numbers were initially developed by (Törnqvist, 1936) and Theil (1967), who were pioneers in the field. A popular metric that is utilized in the process of determining the overall effectiveness of a production system is known as Total Factor Productivity (TFP).

Caves, Christensen, and Diewert (1982) were the ones who initially presented the Malmquist Productivity Index (MPI), which is a dynamic measurement. Taking into account both technological advancements and improvements in efficiency, it analyzes how productivity has changed over the course of time. Within the context of panel data, MPI is frequently utilized because it offers a full evaluation of the dynamics of productivity over a series of successive time periods. Both the frontier shift and the catching-up analysis method concentrate on the changes that occur over time in the distance that separates the observed production points from the production frontier. The concept of catching-up was suggested by (Färe et al., 1983; Färe et al., 1985). This concept investigates whether or not units with lower efficiency are getting closer to the efficient frontier. A better understanding of the dynamics of efficiency changes and technological advancement can be gained via the use of these tools.

According to Kumbhakar and Lovell (2000), parametric distance functions, which include the Distance Function and the Directional Distance Function, integrate a particular functional form in order to predict efficiency scores. Particularly useful in circumstances where there are differences in the prices of inputs and outputs between units, they are relevant. The techniques of bootstrapping, which were first presented by Efron and Tibshirani (1993), include resampling the data that has been seen in order to produce a distribution of efficiency scores. When it comes to establishing confidence intervals around efficiency scores, reducing statistical uncertainty, and improving the robustness of efficiency assessments, bootstrapping is an extremely useful technique. In order to account for errors in efficiency measurement, fuzzy logic methods, which were pioneered by Zadeh (1965), are utilized. Using these methods, degrees of membership are assigned to observations based on how close they are to the efficient frontier. This allows for a more flexible portrayal of efficiency. There has been a rise in interest in the field of efficiency measurement for the use of machine learning techniques, such as artificial neural networks and support vector machines. In their 2017 study, Toloo and Salimi employed a model for efficiency evaluation that was based on support vector machines. They highlighted the capability of machine learning to capture complicated interactions between inputs and outputs in high-dimensional datasets.

In conclusion, the unique character of production processes and data structures that are faced in many industries is reflected in the several ways to measuring technical efficiency that are available. Researchers and practitioners have access to a vast toolbox, which enables them to select methodologies that are in accordance with the features of the data and the particular objectives of the research. The depth and reliability of technical efficiency assessments in a variety of applications can be improved by combining numerous methodologies or by conducting sensitivity analysis.

Through the application of technical efficiency analysis to a variety of agricultural settings, empirical studies have provided insights into the usage of resources and the productivity of agricultural operations. Research conducted by Coelli, Rao, O'Donnell, and Battese (2005) utilized DEA to evaluate the technical performance of rice farms in Bangladesh. The research was conducted in Bangladesh. Researchers discovered significant differences in the levels of efficiency among farms, highlighting the significance of gaining an awareness of and making improvements to technical efficiency in order to ensure the production of rice in a sustainable manner.

5.3.2.1 Constant Returns to Scale and Variable Returns to Scale DEA Model

The Constant Returns to Scale (CRS) Data Envelopment Analysis (DEA) model assumes that the scale of operations remains constant across all DMUs. This means that any observed differences in efficiency are attributed solely to the managerial and operational effectiveness of each unit, rather than variations in the scale of production or resource utilization. The CRS DEA model is particularly useful in situations where the scale of operations is assumed to be fixed or when comparing similar-sized entities (Färe et al., 1983).

On other hand, Variable Returns to Scale (VRS) Data Envelopment Analysis (DEA) model allows for the examination of both technical efficiency and scale efficiency separately. This means that observed inefficiencies can be attributed not only to managerial and operational effectiveness but also to variations in the scale of operations or resource utilization. The VRS DEA model is particularly valuable when analyzing DMUs with different sizes or when the assumption of constant scale may not hold. By decomposing overall efficiency into technical and scale components, the VRS DEA model offers a more nuanced understanding of performance, assisting decision-makers in identifying whether inefficiencies arise from suboptimal management practices or the need for adjustments in the scale of operations (Banker et al., 1984).

5.3.2.2 Input and Output Orientations

Data Envelopment Analysis (DEA) models can be classified into input-oriented and output-oriented variants, each providing a distinct perspective on efficiency evaluation. In the input-oriented DEA model, the focus is on minimizing the inputs required to produce a given level of outputs. This model helps identify the extent to which a decision-making unit (DMU) can decrease its input usage while maintaining the same level of output.

On the other hand, the output-oriented DEA model emphasizes maximizing the outputs produced with a given level of inputs. It assesses the efficiency of a DMU by evaluating how well it utilizes its input resources to generate the maximum possible level of output. These two perspectives allow analysts and decision-makers to gain insights into whether improvements should be directed towards input reduction or output expansion for optimal resource utilization. (Coelli & Perelman, 1999).

Input-oriented Data Envelopment Analysis (DEA) models find application in scenarios where the primary concern is the efficient use of input resources. These models are chosen when organizations aim to minimize input usage while maintaining a predefined level of outputs. This approach proves valuable in optimizing resource utilization, reducing costs, and improving overall operational efficiency. Organizations with a cost reduction focus often prefer input-oriented DEA models as they help identify opportunities to streamline resource expenditures without compromising output levels. Additionally, in situations where the level of output is fixed due to market demands or other constraints, an input-oriented approach is more appropriate. (Lansink et al., 2002).

5.3.2.3 Measuring Input Specific Technical efficiency

The measurement of input specific technical efficiency is related to the concept of input sub-vector efficiency which was introduced by Färe et al, (1994). The input sub-vector efficiency measures the efficiency of a subset of inputs used in the production process rather than the vector of all inputs (Kapelko, 2018). Since its development, other studies that have used the concept of input sub-vector include (Chen et al. 2005; D'Haese et al. 2009; (Coelli & Perelman, 1999)

Alternatives to measuring input-specific efficiency is using the Multi-directional Efficiency Analysis (MEA) developed by Asmild et al. (2003) following the work of (Bogetoft & Hougaard, 1999)Unlike DEA, MEA selects benchmarks such that the input reductions or output expansions are proportional to the potential improvements on efficiency identified by considering the improvement potential in each input or output separately (Asmild & Matthews, 2012).

Another type of input specific efficiency measurement is the Russell-type measure of inefficiency developed by Färe and Lovell (1978). The Russel-type measure minimizes the mean of the reductions in each input dimension. As input and output decisions are not separable at the farm level, a Russell-type measure is straightforward for measuring technical efficiency with respect to inputs and output efficiency. The Russell-type measure allows a nonproportional increase and reduction of the separate inputs of interest (Färe et al., 1994).

Depending on the researcher and the purpose of the study, measuring efficiency can be output-oriented or input-oriented. The former measures the extent to which a firm can increase output, fixing the input vector, whereas the latter measures the potential of a firm to reduce input without changing the output vector. As rational decision makers operating in competitive markets, farmers try to maximize economic performance by producing the maximum feasible output with the minimum input requirements. Hence, a simultaneous expansion of outputs and contraction of inputs has to be considered. To achieve this, a directional distance function will be employed in this study. To sum up, the aim of the research reported in this thesis is to tackle the already mentioned dilemma regarding the impact of precision agriculture on technical efficiency of nationally representative sample of Italian farmers. In particular, starting from the previous efficiency literature, how the digital innovations affect the efficiency of farming was examined, also investigating the crop factors affecting precision agriculture adoption are studied. From a methodological point of view, a DEA approach is implemented on a sample of Italian farms (producing different crops), using data from the Farm Accountancy Data Network, over the period 2017-2020, following the method proposed by (Carrer et al., 2022; DeLay et al., 2022; Finco et al., 2021; Forleo et al., 2021). The DEA is relatively flexible in that it can easily relate multiple inputs to multiple outputs while imposing no assumptions about the functional form of the production technology and efficiency distribution (Iráizoz et al., 2003). In addition, DEA models are constructed to adhere to the underlying production economic theory. This study argues that the advantages of imposing adherence to the production economic theory outweigh the benefits of measuring statistical noise. Therefore, this study deems it appropriate to use DEA for computing the input-specific technical efficiency of Italian farms adopting and non-adopting precision agriculture technologies.

Chapter 6 Technical efficiency of Italian farms adopting and non-adopting precision agriculture technologies: specific-input analysis

6.1 Introduction

Over the course of human history, the agricultural and food industry has been an essential component of human survival, serving as a source of nutrition and nourishment for people all over the world. In spite of this, the contemporary issues that this industry is currently facing, such as climate change, the depletion of resources, and food insecurity, call for the development of novel solutions in order to guarantee its continued viability. In the midst of these issues, digital and environmental innovations are two crucial areas that have the potential to help to the creation of sustainable business strategies in the agri-food industry. Precision agriculture is a significant technology innovation that has the potential to completely transform the way farming is done. A key component of precision agriculture is the utilization of data-driven insights and cutting-edge instruments, such as global positioning systems (GPS), sensors, and drones, to achieve optimal crop management. The primary objective is to provide farmers with the means to improve crop production while simultaneously conserving resources and minimizing waste. Many farmers, particularly in regions such as Italy, have found that the implementation of precision agriculture technologies has proven to be a difficulty, despite the fact that these technologies provide a number of promising benefits. The agricultural industry in Italy is of major economic importance, as it contributes more than two percent to the gross domestic product (GDP) of the country. Understanding the ways in which precision agriculture affects technical efficiency in the context of Italy's agricultural practices is of utmost importance in light of the economic significance of the agricultural sector. Data envelopment analysis, often known as DEA, has emerged as a significant approach for evaluating the impact that precision agriculture has on the efficiency of technical processes (Liu et al., 2013).

A non-parametric method known as decision-making analysis (DEA) is utilized in order to assess the relative technical efficiency of decision-making components that are contained within a specific group that is referred to as decision-making units (DMUs). In spite of the fact that DEA is a well-established method, there is still a requirement for a more in-depth investigation of the ways in which precision agriculture affects technical efficiency within the context of this methodology. Consequently, the fundamental objective of this research is to work toward bridging this gap by pursuing two primary goals. In the first place, the purpose of the research is to determine the level of technological efficiency of Italian farms by utilizing data envelopment analysis to differentiate between farms that have adopted precision agricultural technologies and those that have not adopted these technologies. The results of this analysis offer light on the influence that the adoption of precision agriculture has had on the overall performance of these farms, providing insights into the comparative efficiencies of different agriculture operations. The second objective of this study is to investigate the impact that the implementation of precision agriculture has on the technical efficiency of farming activities, while taking into account a number of different factors, such as gender, age, diversity, and organic farming. Specifically, this entails making use of Ordinary Least Squares (OLS) regression in order to identify the complex correlations that exist between the implementation of precision agriculture and the efficiency of technological processes, while taking into account any potential confounding factors.

In addition to the direct consequences that this discovery has for Italy's agricultural economy, the significance of this research extends further. It could contribute to the development of global strategies for the implementation of technology for precision agriculture and the impact that these technologies have on the effectiveness of farming operations. As the globe struggles to meet the challenge of feeding a growing population while simultaneously reducing the negative impact that agriculture has on the environment, emerging solutions such as precision agriculture are becoming an essential part of the conversation about maintaining sustainable food supply.

Precision agriculture, which is focused on the utilization of data-driven technologies, provides farmers with the opportunity to make well-informed decisions regarding their crops, the distribution of resources, and the general management of their farms. The implementation of global positioning system technology enables accurate mapping and monitoring of fields, which in turn enables farmers to optimize planting patterns and reduce the number of resources that are used that are not essential. The use of sensors provides real-time data on the state of the soil, which enables targeted irrigation and fertilizer delivery, hence increasing the efficiency with which resources are utilized.

Furthermore, the utilization of drones in precision agriculture provides a bird's-eye perspective of the entire farm, which makes it easier to identify crop diseases, pest infestations, and other concerns that may have an impact on productivity. This early intervention not only minimizes crop losses, but it also reduces the need for excessive pesticide use, which contributes to farming techniques that are more sustainable and favorable to the environment. Although there are potential benefits associated with precision agriculture, there are also several obstacles that must be overcome before it can become widely adopted. The initial expenses that are connected with integrating these technologies, in addition to the requirement for specialized expertise and training, create barriers for a significant number of farmers. In Italy, where agriculture plays a significant part in the economy of the country, it is absolutely necessary to have a knowledge of the dynamics of the adoption of precision agriculture and the impact that it has on the efficiency of technical processes.

The research approach that was utilized in this study, which included the utilization of data envelopment analysis (DEA) and Ordinary Least Squares (OLS) regression, offers a solid framework for the investigation of the intricate relationship that exists between precision agriculture and technical efficiency. Because it is a non-parametric method, DEA makes it possible to conduct an all-encompassing evaluation of the relative efficiency of farms by taking into consideration a multiplicity of inputs and outputs. Choosing this methodological approach is in line with the requirement for a more nuanced comprehension of the ways in which precision agriculture affects the technical efficiency of farms in Italy.

The distinction between those who have adopted precision agricultural technologies and those who have not adopted them makes it possible to conduct a targeted examination of the influence that these innovations have had on the performance of farms. The purpose of this research is to determine whether or not the implementation of precision agriculture results in observable enhancements to the overall efficiency of farms by comparing the technical efficiency scores of these two groups. This comparison is essential for policymakers and other stakeholders who are looking for evidence-based insights on the viability and effectiveness of precision agriculture in improving agricultural sustainability. In addition, the utilization of optimal least squares regression makes it possible to conduct a more in-depth investigation into the elements that influence technical efficiency beyond the implementation of precision agriculture. The research aims to separate the unique contributions of precision agriculture to efficiency increases by controlling for variables such as gender, age, diversification, and organic farming. This will allow the researchers to better understand the relationship between them. Due to the fact that this multivariate method acknowledges the complexity of the elements that influence farming practices and outcomes, it provides the study with additional nuance.

As the research progresses, it is expected to make a contribution not only to the academic knowledge of the influence that precision agriculture has on technical efficiency, but also to the practical assistance that is provided to farmers, policymakers, and industry stakeholders. It is possible that the findings will be used to guide targeted interventions and support mechanisms that will facilitate the adoption of precision agriculture, thereby addressing hurdles and offering farmers the greatest possible benefits.

In conclusion, the agricultural and food industry is currently at a crucial crossroads, where it is forced to contend with issues that call for creative solutions. With its emphasis on digital technologies and environmental improvements, precision agriculture emerges as a promising route for improving the sustainability and efficiency of farming methods. This is because precision agriculture is bringing about environmental breakthroughs. The purpose of the research that is presented here is to shed light on the unique implications that the adoption of precision agriculture should have on the technical efficiency of Italian farms. This research aims to provide significant insights that have larger significance for agriculture around the world. In light of the fact that the world is looking for sustainable ways to satisfy the ever-increasing need for food, it is becoming increasingly important to comprehend and make use of revolutionary technologies such as precision agriculture in order to ensure the continued existence of agriculture and the survival of humans.

6.2 Methods

This study used the data envelopment analysis (DEA) model to calculate input-specific technical efficiency scores for a sample of 17,088 observations. Labour, input costs, capital, and land were the four inputs taken into consideration, and revenue was the output. The four inputs considered were labor, input cost, capital, and land, and the output was revenue. Capital (aggregate), input cost and revenue were deflated to 2017 as a base year using ISTAT information. The second analysis used ordinary least squares (OLS) linear regression to investigate the effect of precision agriculture adoption on technical efficiency while controlling for other factors such as gender, age, diversification, and organic farming. Controlling these variables allows for the evaluation of the specific effect of precision agriculture adoption on technical efficiency, resulting in a more precise understanding of its impact (Simar & Wilson, 2007)

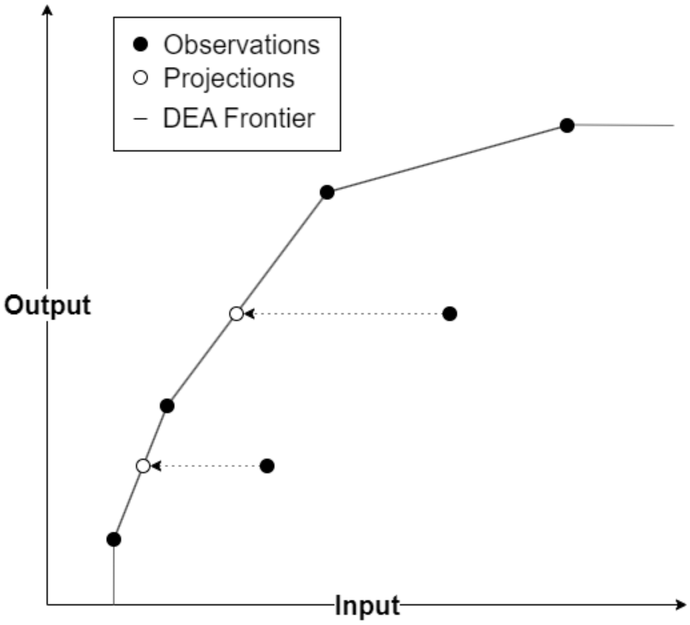

Figure 6.2 Input specific technical efficiency DEA model

6.3 Data description

The data were obtained from an unbalanced panel of Italian farms producing different crops (cereals, vineyards, and legumes) and covering the period 2017-2020. The data have been extracted from the Farm Accountancy Data Network (FADN), which consists of an annual survey aimed to provide representative data, harmonized among EU member states, along three dimensions: region, economic size, and type of farming. The data were pre-processed by excluding observations with null or inconsistent values on the main variables of interest. This led to a dataset of 17,088 observations from 7,128 farms. There were only 37 farms (principal cereals) that have adopted precision agriculture technology and adoption frequency is increasing with increased in a year. The descriptive statistics of the variables in the dataset are illustrated in table 01.

Table 6.1 Data Descriptive statistics

Variable and abbreviation		Description (input and output)	Mean	Standard Deviation
X1	Land	Utilized agricultural area/Land (ha)	17.93	29.33
X2	Input cost	Intermediate inputs (EUR)	8881.45	20312.96
X3	Capital	Amount of capital (EUR)	205157.55	556064.3
X4	Labour	Total number of hours worked per year/ (h)	409.34	667.39
Y	Revenue	Total products sale (EUR)	21032.53	43856.433

There are four inputs viz; Utilised Agricultural Area abbreviated as UAA land), capital, input costs(intermediate inputs), and Annual work unit abbreviated as AWU (labour) while single aggregated output is represented by the sale of products. Land is measured in hectares and represented by the Utilised agricultural area (UAA). Capital is an aggregate, measured in euros, formed by manufactured buildings, machines, tools, plants, and bank cash, and deflated to 2017 as a base year using input prices from ISTAT. Input costs, measured in euros refer to expenditures on water, seeds and seedlings, pesticides and herbicides, feed, forages and lettuce, mechanization, energy (electricity and fuels), passive rentals, and other generic expenses and also deflated to 2017 using agricultural input data available at ISTAT (in Italian: Istituto nazionale di statistica) and in English Italian National Institute of Statistics . Labour refers to the total number of hours worked per year in grape growing. Output consists of products sale, which is also deflated to 2017, with the price index for agricultural output using ISTAT information.

Table 6.2 Year-wise Precision agriculture adopted and non-adopted farms

Year	Variable Precision agriculture (PA)		Total
	0 (not adopted)	1 (adopted)	
2017	4111	4	4115
2018	4215	6	4221
2019	4402	11	4413
2020	4323	16	4339

Total	17051	37	17088

As depicted in table 6.2, there are thirty-seven (37) farms that adopted precision agriculture technology and adoption frequency is increasing with increased in a year.

Table 6.3 Descriptive statistics of the variables used for the OLS

Variable and abbreviation	Description	Mean	Standard Deviation
PA	Precision Agriculture	0.0021653	0.0464833
Male	Gender	0.7933638	0.4049041
Young	age	0.1133544	0.3170348
Diversified	Non-farming activities on agricultural land	0.1404494	0.3474629
Organic	Mode of production	0.1688904	0.3746661

Results and Discussion

6.4 Results and discussion

The results of the technical efficiency analysis using the input-oriented DEA model revealed that the firms' mean technical efficiency is low, at 0.509, meaning that they are utilizing technology at only 50% of its potential. Moreover, only 152 observations out of 17,088 have an efficiency score of 1, indicating that they are performing at their highest level of efficiency.

Table 6.4 Results of Input specific Technical Efficiency scores (DEA model)

Efficiency range	Number of farms	Percentage
0<= E <0.1	38	0.22
0.1<= E <0.2	406	2.38
0.2<= E <0.3	1580	9.25
0.3<= E <0.4	3300	19.31
0.4<= E <0.5	3624	21.21

0.5<= E <0.6	3031	17.74
0.6<= E <0.7	2338	13.68
0.7<= E <0.8	1415	8.28
0.8<= E <0.9	886	5.18
0.9<= E <1	318	1.86
E ==1	152	0.89
Min. 1st Qu. Median Mean 3rd Qu. Max. 0.002052 0.371279 0.487802 0.509169 0.631432 1.000000		

Furthermore, the distribution of efficiency scores showed that only a small percentage of observations have high technical efficiency scores. With the highest percentage of firms lying in the 0.4 to 0.5 range (21.21%), approximately 38 observations (0.22%) have a score of 0 to 0.1, 406 observations (2.38%) have a score of 0.1 to 0.2, and so on. This distribution suggests that there is an enormous potential for farms to increase their efficiency by adopting precision agriculture techniques.This study may also suggest that there are two primary ways in which precision agriculture technology can affect technical efficacy. First, by reducing overlap and saving fuel, chemicals, and time in the field without compromising yield, it can improve input utilization. For instance, GPS auto-steer minimizes repetition and conserves resources. Second, information-intensive technologies provide field data that affect decisions about input utilization for specific sites. For example, precise nutrient application rates are determined by detailed soil nutrient maps, which lower fertilizer costs while keeping or even increasing output. Therefore, investments in precision agriculture technologies can assist farms in maximizing input use, reducing waste, and increasing production, which will result in better technical efficiency scores, increased profitability, and increased market competitiveness.

Nevertheless, farms that have already attained a high level of technical efficiency might not be ready to invest in these technologies owing to the higher implementation costs or a lack of knowledge of the advantages of precision agriculture. Thus, to improve technical efficiency and sustain market competitiveness, policymakers and industry stakeholders should inform and encourage businesses to embrace precision agriculture practices.

The results of the OLS regression model demonstrated that the adoption of precision agriculture technologies has a significant effect on technical efficacy. The coefficient of the "PA" variable is estimated to be 0.074046, indicating that the adoption of precision agriculture technologies increases technical efficiency, holding all other variables constant. This coefficient is statistically significant at the 5% level, indicating that the adoption of precision agriculture technologies can contribute to improving technical efficiency.

Table 6.5 Results of OLS Regression

	Estimate	Std. Error	t value	Pr(>|t|)

(Intercept)	0.513210	0.003222	159.292	<2e-16 ***
PA	0.074046**	0.030075	2.462	0.0138 *
Male	-0.044171***	0.003459	-12.771	<2e-16 ***
Young	0.024391***	0.004440	5.493	4e-08 ***
Diversified	0.003067	0.004030	0.761	0.4466
Organic	0.055119 ***	0.003764	14.645	<2e-16 ***

To sum up, knowing the effect of precision agriculture technologies on the technical efficiency of farms can help policymakers, investors, and farmers collaborate to encourage the adoption of these technologies and support the agri-food sector's transition to a more sustainable and prosperous future.

Chapter 7 General Discussion and Conclusion

Despite recent growth in the scientific literature on precision agriculture technologies adoption in agricultural economics, no studies have conducted on the effects of precision agriculture technology on technical efficiency using Italian FADN sample data (Carrer et al., 2022; DeLay et al., 2022; Finco et al., 2021; Forleo et al., 2021). It is essential for policymakers who are interested in enhancing the economic and environmental sustainability of producers to have a comprehensive understanding of the implications that the adoption of precision agricultural technology has on farm performance and the utilization of inputs. Given the growing investments in technology adoption policies across European countries, this becomes even more relevant than it already was. As a result, the purpose of this thesis is to investigate the complex dynamics that govern the way in which precision agriculture influences the production and technical efficiency of agricultural farms.

For this purpose, Chapter 02 of this work briefly summarises the agricultural 4.0 and precision viticulture technologies and their relative applications. Afterwards, of diffusion of innovation process is described. Later, the theoretical literature has been analysed as concerns the estimation of the production frontier. Finally, the effect of precision agriculture on technical efficiency and theoretical frameworks has been reviewed. From a theoretical point of view, adopting precision agriculture might be an effective strategy for improving farm performances by lowering the usage of inefficient inputs, therefore impacting economic and environmental farm achievement (Forleo et al., 2021).

Having noted this literature gap, combined with the lack of studies aiming to investigate the impact of technology adoption on technical efficiency (Vigani and Kathage, 2019), a case study has been carried out to measure the relationship between precision agriculture, input use and farm performances in the Italian farms. According to the conclusions of the case study, which are elaborated upon in Chapter 06, there is an urgent requirement for more investment in novel approaches to agricultural innovation. It is clear from the findings that expenditures of this kind are necessary not only for improving the overall performance of farms but also for ensuring that they remain competitive throughout the market. The purpose of the case study is to provide as a practical demonstration of the theoretical underpinnings that were discussed in earlier chapters. It also provides tangible evidence of the positive influence that precision agriculture can have on the overall efficiency and sustainability of agricultural businesses.

Nevertheless, it is of the utmost importance to recognize the constraints that are inherent in this study. When it comes to the practical implementation of this research, the consideration of intermediate input consumption as a solitary variable is the fundamental limitation that arises. Because of this constraint, it is more difficult to determine which particular precision agriculture technology has the most significant impact on technical efficiency. As a consequence of this, the research does not adequately investigate the complex connections that exist between the various precision agricultural technologies and the intermediate inputs that are utilized for certain crops. As a result of the varied characteristics of these production inputs and technologies, it is absolutely necessary to do additional study in order to decipher the deep linkages that are included within this complicated structure.

In conclusion, the purpose of this thesis is to investigate the impact that the adoption of precision agricultural technology has on the technical efficiency of Italian farms in order to fill a significant gap that currently exists in the existing body of literature. The research highlights the significance of adopting technological breakthroughs for the purpose of improving agricultural practices by conducting a thorough investigation of theoretical frameworks, conducting a case study with great attention to detail, and conducting a critical analysis of the limitations of the study. It is becoming increasingly important for policymakers, researchers, and practitioners alike to have a comprehensive understanding of the various implications that precision agriculture has on farm performance. This understanding will play a significant role in determining the trajectory of sustainable agriculture in the 21st century.

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