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Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture

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ABSTRACT

The term “Agri-Food 4.0” is an analogy to the term Ïndustry 4.0, coming from the concept “agriculture 4.0”. Since the origins of the industrial revolution, where the steam engines started the concept of Industry 1.0 and later the use of electricity upgraded the concept to Industry 2.0, the use of technologies generated a milestone in the industry revolution by addressing the Industry 3.0 concept. Hence, Industry 4.0, it is about including and integrating the latest developments based on digital technologies as well as the interoperability process across them. This allows enterprises to transmit real-time information in terms behaviour and performance. Therefore, the challenge is to maintain these complex networked structures efficiently linked and organised within the use of such technologies, especially to identify and satisfy supply chain stakeholders dynamic requirements. In this context, the agriculture domain is not an exception although it possesses some specialities depending from the domain. In fact, all agricultural machinery incorporates electronic controls and has entered to the digital age, enhancing their current performance. In addition, electronics, using sensors and drones, support the data collection of several agriculture key aspects, such as weather, geographical spatialization, animals and crops behaviours, as well as the entire farm life cycle. However, the use of the right methods and methodologies for enhancing agriculture supply chains performance is still a challenge, thus the concept of Industry 4.0 has evolved and adapted to agriculture 4.0 in order analyse the behaviours and performance in this specific domain. Thus, the question mark on how agriculture 4.0 support a better supply chain decision-making process, or how can help to save time to farmer to make effective decision based on objective data, remains open. Therefore, in this survey, a review of more than hundred papers on new technologies and the new available supply chains methods are analysed and contrasted to understand the future paths of the Agri-Food domain.

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1. Introduction

Small farms are the engine to support rural employment and to make a considerable contribution to territorial development. Even though they have always been considered a cornerstone of agricultural activity in the European Union (EU), this sector most often suffers from very low efficiency and effectiveness, sensitivity to weather, market disruptions and other external factors, such as poor agriculture supply chain stakeholders' linkages and communication, especially at the food processing level. In fact, and as stablished by the FAO,[1] under an approach from "field to fork" the agriculture supply chain structures can also be named Agri-Food supply chains, where main events coming from the agricultural production of food to the food processing events, including trading, are linked. Across this Agri-Food Supply Chain, in most of the cases, the transferred agriculture knowledge, from generation to generation, is paramount from a cultural point of view, but most of the time, it does not answer to the needs nor the requirements of the Agri-Food Supply Chains. Furthermore, such delineation does not exist also between farms as economic units and farmers who are producing food, mostly, for their own consumption. However, no formal delineation to what is a "small" and/or a "large" farm formally exists that is holistically accepted, it depends on several factors, such as countries, regions, politics, strategies, market shares amongst many others. Nonetheless, there are two criteria to classify farm size: standard output (in economic terms) and utilised agricultural area (UAA), as alternative measure[2] . In this same line, Eurostat[3] predicts that, by 2026, an increment of 4%–6% in agriculture cost savings, as well as an increment of 3 % in market value, will be regarded to the use and development of smart agriculture. Hence, "Agriculture 4.0″ emerges to provide advanced technologies to the famers in order to meet agri-food production challenges, hence, to achieve more affordable prices for open market and the minimum cost for farmers. Thus, the expectation for the further coming years, is that Agri-Food 4.0 should help meeting sustainable challenges by increasing the agri-food supply chain stakeholders revenues as well as decreasing their pressure for handling complex and external factors they cannot control, such as weather, market behaviours and policies, but also to react on time by visualising current trends in needs. This paper focus principally on the factory farm model issued from the European and north American style. In those typologies of farms the Industry 4.0 elements can be introduced and merged with the agricultural domain to create the Agri-Food 4.0. The focus is more specialised on the industrial farming although the Agri-Food 4.0 is started to be adapted also to the organic and silvo-pasture paradigms. Thus, this paper, considering a review over than two hundred papers, provides a contribution to knowledge by establishing the linkages between new 4.0 trends in technologies and Agri-Food Supply Chain Challenges, which opens the 4.0 research field for a multidisciplinary work. The choice of the literature review methodology focused firstly on key words related to the Agri-food technology, then the second approach was to focus on selected journals and at the end we looked for the data-based repository and the linked publications. To accomplish this, the structure in this paper is as follows: in the first place, a compressive state of the art of Agri-Food 4.0 related technologies is covered. In the second place, a review and contribution coming from digital technologies to the new supply chain methods in Agri-Food shows linkages with next trends and technologies. Next, and linked to the agri-food supply chain challenges, the fourth section presents new trends and models in agri-food supply chains, especially in the domain of risk management, collaboration, governance, cold chain management, globalization, information and communication technologies, Logistics, supply chain structures and sustainable agri-food supply chains. Finally, the fifth section covers the main conclusions, visions and perspectives for this novel research.

2. Agri-food 4.0 and technologies state-of-the-art

The agricultural sector has been active in digital innovation for decades already. Especially the advances in Precision Agriculture, remote sensing, robots, farm management information systems, and (agronomic) decision support systems have paved the way for a broad digital transformation in farming and food (Pedro and Gonzalez-Andujar, 2019). Recent developments, such as Cloud Computing, Internet of Things, Big Data, Blockchain, Robotics and Artificial Intelligence, allow for the integration of so far isolated lines of development into smart, connected systems of systems. Those technologies will let the agriculture to evolve in a data-driven, intelligent, agile and autonomous connected system of systems. The operations of each agricultural process will be automatically integrated in the food chain through the semantically active technologies up to the end consumer. The 4th industrial revolution is now reaching agriculture.

The digital platform (DP) concept emerged as an integration of heterogeneous mainly open software solutions for ecosystem building (Yablonsky, 2018). The EU promote the creation of digital platforms for several application domains as manufacturing (i.e. FoF 11 – 2016 projects, DT-ICT-07-2018-2019, etc.), construction (BIM + calls), etc. As a concentration of technology enablers, research on DP covers several issues such as software engineering (Guertin and Van Benthem, 2016; Wang et al., 2006), process simulation and development (Zhao and Yao, 2016; Hu et al., 2016), features analysis (Wang et al., 2014), resource performance (Mocnej et al., 2018), test algorithms (Santiago et al., 2017) or performance control (Sahota et al., 2011).

The technological platforms allow access to the different stakeholders and provide deployment capabilities for IT solutions. These solutions are exposed by service providers or developed by software engineers.

Agricultural Data management and exploitation is the central node between digital transformation capabilities and the agriculture concerns. The main research issues concern the consolidation of data repositories with open data (Gumaste and Kadam, 2016) (weather, maps, etc.), governance data (policies, local regulation,

[1] http://www.fao.org/energy/agrifood-chains/en/ (accessed on 26/08/2019).
[2] https://ec.europa.eu/eurostat/statistics-explained/index.php/Small_and_large_farms_in_the_EU_-_statistics_from_the_farm_structure_survey.
[3] https://ec.europa.eu/agriculture/sites/agriculture/files/statistics/facts-figures/agricultural-farm-income.pdf.

etc.) and domain specific data from end users. Data typology is very rich (land, location, energy, climate, climate impact, etc.) and data volume is continually increasing by the integration of sensors and IoT platforms in agriculture (Amandeep et al., 2017; Biradar and Shabadi, 2017). Data engineering effort covers pattern definition (Laube et al., 2011; Spekken et al., 2016), classification algorithms (Narvaez et al., 2018; Shi et al., 2015; Yalcin and Razavi, 2016), correlation analysis (Nilsson et al., 2016; Xavier et al., 2018; Xie et al., 2017), etc. All those technologies provide engineering capabilities for agricultural data. The implementation of these techniques will handle farmers data, will integrate new data repositories from external providers, will transform data to knowledge and feed decision support systems. The data transparency enabler with necessary sharing policies will accelerate data ingestion and ejection processes.

2.1. Big data technologies

Research activities in Big Data provide relevant results in several application domains (healthcare, marketing, maritime, urban, manufacturing, etc.). The Big Data Value Association (BDVA)[4] promote the application of bigdata in different domains (Belaud et al., 2019). The Big Data Grapes EU project[5] provides data semantic, analytics, integration and exploitation solutions as well as a software stack for grapes agriculture. As additional ongoing research issues, we identified tools and technology development (Devarakonda et al., 2014; Hashem and Ranc, 2016), analytic methods and services (Malhotra et al., 2017; Deka and Walczak, 2017), clustering methods (Balan et al., 2015), transformation algorithms (Penar and Wilczek, 2016; Hashem and Ranc, 2016) performance and data processing technics (Wu and Zhao, 2009), data source and storage management (Cha et al., 2018; RubyDinakar and Vagdevi, 2017), etc.

The integration of Big Data technologies in Agri-Food projects plays an important role in: the extension of farmers data to create new knowledge; the creation of innovative services and processes by IT providers and software developers as well as the extension and the adaptation of ICT and Factories of the Future (FoF)[6] related Big Data models and patterns for agriculture. There are several Big Data Repositories that guarantee, nowadays, the access and the exploitation to Agri-Food data. As example: the “National Climatic Data Centre” (about 2,9 Go per day); Satellite Imagery and metrological information from Google and the NASA Earth Exchange; Soil, water and geospatial data from the National Resources Conservation Service (US); the OpenCorporates as the world’s largest open repository of companies (165 million companies around the word); etc.

2.2. Internet of things technologies

The integration of IoT platforms in agriculture provides additional data sources describing agricultural features (water, soil, humans, animals, etc.) with more data. The recent research issues on IoT highlight the multiplication of IoT platforms. This expansion generates new implementation frameworks (Lee et al., 2018; Choi et al., 2018) answering to different requirement models, new networks of heterogeneous components and sensors with different monitoring models (Pflanz et al., 2018; Vergara et al., 2017; Prathibha et al., 2017), time processing scheme and misbalanced energy consumption (Ruano et al., 2018; Jarolimek et al., 2016). The integration of the IoT platforms with the agricultural issues could add additional research challenges, specifically when the data are stocked or used in the cloud, in terms of interoperability (Panetto, 2007; Mocnej et al., 2018; Zarko et al., 2017; Hefnawy et al., 2017; Martinez et al., 2016; Leal et al., 2019; Panetto et al., 2016) (protocols, security, etc.), performance monitoring (Paulraj et al., 2018; Mekala and Viswanathan, 2017), etc. In addition, IoT serves Robotics (Murar and Brad, 2015) and Automated Guided Vehicles (AGV) (Sanchez-Hermosilla et al., 2013).

An interesting activity might be the benchmarking of all the existing IoT platforms and their proposed functionalities and mapping them with Agri-Food stakeholders’ requirements. The integration of IoT capabilities will support farmers in the harvesting of new data sources to create new valuable services.

2.3. Knowledge model approaches

The development of valuable knowledge models in agriculture aims to transform shared multi-sources data repositories to create profitable services and support the decision making for different stakeholders. Recent research topics address precise data collection and engineering to serve knowledge creation of new farming models (Abdullah et al., 2017; Irmak et al., 2006), technology application in farming (Chen and Jin, 2011; Gerhards et al., 2012; Singh et al., 2013), resource allocation (Garcia et al., 2005; Jang et al., 2017; Musacchio and Grant, 2002), assessment frameworks (for risk, policies definition and quality management) (Jacxsens et al., 2016; Louwagie et al., 2012) as well as the qualification of decision models (Costanzo and Faro, 2012; Dragincic et al., 2015) and the identification of decision parameters (region, land, climate, plant, time, process, etc.).

2.4. Artificial intelligence techniques

Artificial Intelligence (AI) techniques propose important contributions to knowledge model’s identification, service creation and the decision-making processes as support for the different Agri-Food’s applications (Solemane et al., 2019). AI offers formal general algorithms for prediction (Bhatt and Buch, 2015; Soh et al., 2018), accuracy and performance evaluation (Jeon et al., 2017) as well as pattern classification (Ott et al., 2003; Pinho et al., 2011; Starr, 2005) that might solve knowledge issues in the agricultural domain such as the pest’s identifications and the correct treating methods. In addition, AI supports applications in farming technics development: land allocation regarding the targeted activity (Pokhrel et al., 2018), irrigation process analysis and control (Ait-Mouheb et al., 2018; Mohanraj et al., 2017), robot guidance (Tian et al., 2018; Roshanianfard et al., 2018; Sheridan, 2016), etc.

2.5. Smart agriculture

Smart agriculture emerges as a main concept in Agri-Food 4.0. By integrating new technology enablers propelled by the Industry 4.0 paradigm (Annosi et al., 2019), smart agriculture addresses important farming objectives as water saving (O’Connor and Mehta, 2016), soil conservation (Li et al., 2002), limit carbon emission (Ochoa et al., 2014) and productivity increasing (Mayer et al., 2015) by doing more with less. The new agricultural age aims to harmonize and share better local European policies and rules to scale the best farming practices and applications. Smart agriculture offers the opportunity to farmers, technology and service providers, governance agencies and other impacted stakeholders (financial organization, investors, traders, etc.) to share their experiences and preoccupations in the optimization in the farming Supply Chain

[4] http://www.bdva.eu/.
[5] http://www.bigdatagrapes.eu/.
[6] http://ec.europa.eu/research/industrial_technologies/factories-of-the-future_en.html.

with the close respect of production sustainability (Swisher et al., 2018; Oberholster et al., 2015).

2.6. Precision farming techniques and robot development

The Precision Farming topic is already covered by other H2020 calls (SFS-05-2017, SFS-06-2018-2020, SFS-08-2018-2019, etc.). The analysis of released projects outcomes and related research issues allows to identify new technologies, processes and applications in agriculture. Relevant models are proposed for land, grain and arable related activities (Gumma et al., 2016). Relevant listed results cover harvesting distribution accuracy (Roshanianfard et al., 2018; Kamata et al., 2018; Alzahrani, 2018), cost development (Pomar et al., 2010) and distribution optimization (Zhou et al., 2018; Tabatabaie et al., 2013; Ruiz-Garcia et al., 2010; Eisele et al., 2001).

Within the Agri-Food projects is planned to reuse available precision farming technologies and results to improve the quality of targeted farmers' processes and applications. Results in the integration of robots in agriculture are well mature and already proposed by Agri-Food stakeholders. With precision farming enablers, it will be ensured the performance of impacted farming processes.

Agriculture Robots are already investigated in the precision farming topic. Recent research in this area covers the adaptability of robot design to the agriculture sector, the improvement of navigation conditions through additional sensing (Liu et al., 2018; Tao et al., 2017; Jhonattan et al., 2019) and localization capabilities as well as real-time image processing (Xu et al., 2017; Pilli et al., 2015) and camera detection (Dworak et al., 2013) to maximize the operational capabilities and behaviour of robots and collaborative robots (cobots). Robots can assist humans (Chilcanan et al., 2017; Dondeynaz et al., 2013) for difficult tasks or replace them for difficult ones. The cost reduction (Pomar et al., 2010) effectiveness is demonstrated and research in decision error reduction (Montecinos et al., 2018; Shin and Ko, 2017; Brigido et al., 2015) is intensive to improve accuracy by simulation (Xu et al., 2018; Wang et al., 2018; Latorre-Biel et al., 2018) and by more precise path finding (Spekken et al., 2016; Nolan et al., 2017) and guidance algorithms (Kviz et al., 2014; Baio, 2012). The new Agri-Food projects fund the integration of Agriculture Robots to support the applications since the beginning to ensure the maximum results.

Building resilient and sustainable farming system is the ultimate concept behind Agriculture 4.0. Recent research in this topic covers farming processes sustainability analysis (McGuire and Sperling, 2013; Joly, 2005), farming activity calibration (Suryoputro et al., 2017; Hosseini et al., 2014; do Nascimento et al., 2012) (rotation cycles, control of accuracy), the development of conservation protocols (Kladivko et al., 2014; Gaspary et al., 2002) and the alignment of business development strategies.

3. How the new digital technology transforms the agri-food supply chains

To achieve robust, resilient and sustainable agri-food supply chains is very complex because they face more sources of uncertainty and risks in comparison with other supply chains that give rise to serious questions and concerns about their economic, environmental and social performance. Several studies identify agricultural sources of uncertainty (Mundi et al., 2019; Esteso et al., 2017; Esteso et al., 2018) and how to model them (Grillo et al., 2019). In Esteso et al. (2018) four types of crop-based uncertainty are identified: Product (shelf-life, deterioration rate, lack of homogeneity, food quality and food safety), Process (harvesting yield, supply lead time, resource needs, production), Market (demand, market prices) and Environment (weather, pests & diseases and regulations). Poor management of these sources of uncertainty can have a very negative impact on safety, quality, quantity and waste of products as well as human, technological and natural resources. Indeed, the agri-food sector is one of the economic and political areas worldwide, with key implications in sustainability to cover not only the food needs of the population, contribute to their employability and economic growth, but also in the impact on the natural environment (Iakovou et al., 2014).

Therefore, the agri-food supply chains are strongly pressured to manage these sources of uncertainty and risks whose precise evolution over time is unknown but may jeopardize the future sustainability of these type of supply chains. It is necessary to move away from "business as usual" developing new solutions and implement innovative technologies (FAO, 2018). Along these lines, a digitalized supply chain, allows companies to monitor material flows in real time making potential risks visible and develop future plans to face them. The main drivers for the digitalization of the processes of SC are usually the increase of the flexibility and the speed of reaction of the industrial/logistical systems (ten Hompel and Henke, 2017a, ten Hompel and Henke, 2017b) as well as the improvement of agri-food supply chain robustness and resilience.

In this context, data becomes crucial. Data is the lifeblood of any business and the agricultural business is not an exception but rather a referent. The new technologies have a great impact on the reduction of uncertainty since they allow obtaining precise data in real time, whose treatment, together with the capacities of autonomous and intelligent decision making will help to increase the efficiency, sustainability, flexibility, agility, and the resilience along the whole supply chain from the farmers to the final customers.

In the context of data-driven supply chains, the new technologies listed in the previous section, provide different and complementary support to the sequence of activities from data chain (Wolfert et al., 2017): data capture, storage, transfer, transformation, analytics and marketing. The support of each technology to different data chain activities lets envisage that the true potential of the data comes from the combination and integration of these technologies. Indeed, each one will improve some of the following basic functions of agri-food supply chains: sensing, monitoring, control, analysis (descriptive capabilities), prediction (predictive capabilities), decision-making (prescriptive capabilities) and adaptive learning. Through the sensing, monitoring, control and analysis it is possible to the early and accurate detection of problems and even predicting them before occurring, making better decisions and learn of them improving the sustainability and resilience of agri-food supply chains.

In fact, the integration of previous technologies allows a more intelligent management of the agri-food supply chains, being able to combine multiple models of independent data analysis, repositories of historical data and data flows in real time. Real-time information and data processing tools provide new opportunities for companies to react more quickly to changing conditions in the supply chain. Due to this integrated intelligence, the agri-food supply chain management goes from supporting decisions to delegating them and, ultimately, to predicting which decisions should be taken.

From all the above, there is no doubt that these new technologies are transforming the way agricultural sector organize and make decisions. In order to provide a general overview about how the new digital technology transforms the agri-food supply chains, the tables (Tables 1–4) integrate and classify the main positive impacts of the most relevant technologies as well as the challenges to be faced according to recent studies in the field carried by different authors.

As it can be seen in the above tables, some challenges of these digital technologies appear as strengths of others. This allows intuiting the suitability of using them as complements with the others.

Table 1
IoT: Impact and Challenges.

Internet of Things	
References	(Riggins and Wamba, 2015; Nukala et al., 2016; Brewster et al., 2017; Khan and Ismail, 2017; Luque et al., 2017; Gómez-Chabla et al., 2019; Shi et al., 2019)
Impact	**Functional impact:** • Allows sensing of crops • Real time and remote monitoring of environment (temperature, humidity. . .), pests, diseases, etc, report conditions, alter its state depending upon predefined parameters, alter the state of connected things, and make changes to its surrounding environment. • Increase tracking and tracing of any tagged mobile object • Automatic managing and controlling **Economic impact:** • Increases operational efficiency: lower production costs, increase yield quality/quantity, increase productivity and animal health/welfare. **Environmental impact:** • Enhances farming methods and the real-time control of the cultivations. • Minimizes the ecological footprint and environmental impact of agricultural practice and adapt crop management to requirements of climate change. • Reduces use of water and other natural resources, and improve soil quality • Reduces wastes: logistic and qualitative traceability of food production allows reducing costs and the waste of inputs through the use of real-time data for decision making. **Social Impact:** • Increase of customer satisfaction for the products delivered (it facilitates and enhances food safety, security, quality, freshness) • Ensure that certification schemes (e.g., organic) are effective and fraud-free across the entire food supply chain. • Less manual labour required **Business impact:** • Create new business models (direct relationship with customer) and cooperation opportunities. **Technological impact:** • Low power wireless sensor, • Better connectivity machine to machine
Challenges	**Organizational Challenges:** • Heterogeneity of the sector: no single solution, whether technological, business model, or regulatory, will fit or accommodate the needs of all • Capital investment costs: the challenge is making IoT offerings sufficiently attractive to small scale farmers with limited investment available for new technology • Business models and business confidentiality **Social Challenges** • Lack of technical skill requirement • User and societal acceptance **Technological Challenges** • Automation requires the collection, combination and analysis of data from different data sources, in short, big data analytics. • Hardware and Software Complexity • Lack of interoperability • Lack of connectivity in rural areas • Data processing power: the absence of data processing services significantly hinders IoT • Lack of clear data governance: control and ownership of farm data is still contentious • Data security, privacy and anonymity • Decentralization

Indeed, in the near future, the full potential of data will rely on the combination of the different technologies that enhance data-driven agri-food supply chains more informed, efficient, secure, sustainable and resilient. For instance, IoT and BDA can benefit from blockchain providing data security, anonymity, trust and decentralization. Since blockchain exchange information in a distributed network, novel IoT applications will be developed for distributed environments. On the other side, the valuable data generated from the IoT could enrich transaction details that are registered on the blockchain (Tripoli and Schmidhuber, 2018). In turn, the accurate data provided by blockchain technology can be used as input for AI applications and to also record their outputs (Rabah et al., 2018). Besides, AI can enhance IoT by developing applications to analyse data captured by sensors in real time using machine learning algorithms (Reshma and Pillai, 2018). Machine learning and other analytic methods can also improve predictive and prescriptive capabilities (decision making) of Big Data Analytics.

There is a broad consensus on the need to strengthen research and innovation in the Agri-food sector, both in terms of practices and technologies, through the creation of new products, the improvement of processes, services or processes or the integration of digital possibilities. Indeed, one of the persisting challenges to take advantage of the full potential of the data is to achieve not only the integration of these technologies but also their interoperability. Diversity of stakeholders integrating agri-food supply chains with different interests and characteristics make difficult to find solutions that fit all those involved, so group decision-making tools should be developed (Zaraté et al., 2019). Moreover, when these solutions require significant investments and there are stakeholders, such as small farmers with a limited budget. For this reason, it will be key to demonstrate the value of innovations as compared to their companies and to collect and exchange data. Other challenges reside on the needs of data standards. The standardization of the fruition data would provide equity for all stakeholders because of the possibility to access to the same information that might provide financial gain. The fruition data might provide the training for ensuring the availability of the required technical skills and definition of regulatory actions by governments.

Research may be co-financed with partners private (e.g., companies or business groups), government (many departments and agencies involved) or institutional (e. g. universities). This approach accentuates the effect leverage government support and improve the transfer of innovations to businesses. It enables the training of highly qualified personnel and a new generation of scientists for

Table 2
Blockchain: Impact and Challenges.

Blockchain Technology	
References	(Rabah, 2016; Bermeo-almeida et al., 2017; Ko et al., 2018; Tripoli and Schmidhuber, 2018; Queiroz et al., 2019; Zhao et al., 2019; Guoqing et al., 2019)
Impact	**Functional impact:** • Improve real-time visibility, transparency, security, immutability, irrevocability, neutrality, and reliability for all the supply chain actors • Increase in data quality (ensuring immutable product-process links, smarter and more accessible data and market information) • Improve real-time tracking for the agri-food products and management of defective products. • Improve faster, responsiveness and efficient operations and scalability • Automated certification of food safety and quality **Economic impact:** • Lower transaction costs • Markets can form more efficient prices, as information asymmetries among stakeholders disappear. **Environmental impact:** • Reduction of wastes due to the enhanced traceability. **Social Impact:** • Improves customer satisfaction by ensuring food safety and quality • Disintermediation: no needed for intermediaries and trusted third party due to smart contracts. • Risk reduction of involved actors • Empowered users: users are in control of all their information including better informed consumers **Business impact:** • Process integrity: users can trust that transactions will be executed exactly as the protocol commands removing the need for a trusted third party. • Enhance members' collaboration • Disintermediation & Decentralised operations **Technological impact:** • It addresses challenges on the Internet of Things such as decentralization, anonymity, and security.
Challenges	**Organizational Challenges:** • Uncertain regulatory status and complex legal frameworks. • Environmental Challenges: • Large energy consumption **Social Challenges:** • Lack of required technical skill • Cultural adoption: blockchain represents a complete shift to a decentralized network which requires the buy-in of its users and operators. **Technological Challenges:** • Blockchain integration with other technologies (BDA, IoT, CPS) • Strategize the transition: blockchain applications offer solutions that require significant changes to, or complete replacement of, existing systems. • Limited storage capacity and scalability • Control, security, and privacy: while solutions exist, including private or permissioned blockchains and strong encryption, there are still cyber security concerns that need to be addressed before the general public will entrust their personal data to a blockchain solution. • Throughput and latency issue: in the context of agri-food Supply Chain management, due to the original restriction of block size and the time interval used to generate a new block, the current processing capacity of blockchain cannot fulfil the requirements of processing millions of transactions in real-time • Infrastructure and capacity development challenges: it can only be applied as long as an internet connection is available, which can still be a challenge in some developing countries

companies and centres of research. The stability of funding agreements with the centres promote the retention of their qualified staff and facilitate partnerships with industry for the realization of structuring projects. Access to appropriate funding and research tax credits and development (R&D) is also a source of funding structuring for the industry to absorb financial risks generated by innovation activities (Tuhin et al., 2019). This type of financing is particularly important when innovation takes place directly in the company, which is often the case in food processing.

4. The new models of the Agri-Food supply chains

The competitiveness of food processing companies depends on their investment capacity, the increase in their production, the development of new products and the implementation of processes to stand out from the competition (Guoqing et al., 2020). Over the past 30 years, we have seen a significant reduction in biodiversity, FAO estimates that we will have a 70 % reduction in biodiversity on our planet by 2050 (FAO, 2018). Human activities seem to be the main cause of this loss. The agriculture has many cards in hand to slow this process by implementing environmental protection practices and reducing the chemicals that have led to the destruction of many animals and insects living on land, in the air and in the water; creating green corridors and shelters for animals and insects; the cultivation of old species or species with high genetic variability, leaving the design of hybrid plants and monocultures that lead to significant genetic depletion; the reduction of arable land to make way for the replanting of forests, grasslands and hedges. The competitiveness is addressed to a new way of thinking the Agriculture that will let to optimize the process and respecting the nature. The labour shortage in many regions of Europe requires processing companies to automate and robotize their processes. In addition, investment in these new technologies allows them to improve their productivity and provide better working conditions necessary to the attraction and retention of the workforce. In addition, to meet the quality standards requirements of large chains and food retailers, they must use recognised quality management and traceability systems. Investment in digital technologies also promotes automation of operations, data management and access to a new range of management tools (Industry 4.0). The industry is particularly requested, as shown in the previous section, for the use of digital technologies, which allows it to optimize production and the supply chain while ensuring traceability of food from more and more pointed (Panetto et al., 2019).

Table 3
Big Data Analytics: Impact and Challenges.

Big Data Analytics	
References	(Bronson and Knezevic, 2016; Ribarics, 2016; Wolfert et al., 2017; Kamilaris et al., 2017; Himesh, 2018; Saggi and Jain, 2018; Nguyen et al., 2018; Rabah et al., 2018; Kamble et al., 2020)
Impact	**Functional impact:** • Descriptive analytics allows understand what has happened and, therefore, diagnosis (identify patterns, clustering, identify agri-food risks, benchmarking) • Predictive analytics allows gain insights about what will be happening or likely to happen by exploring patterns in data (forecasting of demand, yield, price, weather, consumer behaviour) • Prescriptive analytics allows make better decisions and influencing what should be happening using mathematical optimization, simulation or multi-criteria decision-making techniques (real-time decision-making, automation of robotics use crop planting and harvesting planning, distributing, network design, risk management, etc.) **Economic impact:** • Improve operational efficiency in general by means automation and better decisions. • Optimum crop planning prescription based on historical agriculture data (crop yield, weather, soil, seed and fertilizer) to enhance farm productivity and profitability. • Better optimized seeds and livestock and new methodologies that improve yields and production. • Faster and cheaper delivery of goods produced to distribution centres and consumers. • Real-time decisions and alerts based on data from fields and equipment. • Integrated production and business performance data for improved decision making. • Rationalized performance data across multiple geographies. • New insurance products **Environmental impact:** • Better resource use (land, water, pesticides. . .) • Minimize food print • Minimize waste **Social Impact:** • Better customer service • Risk reduction • Transformation of traditional skill-based agriculture into digital and knowledge-driven agriculture. **Business impact:** • Major shifts in roles and power relationships between the different players in the Big Data farming stakeholder network. (e.g. between farmers and large corporations) • Development of shorter supply chains and new operating models. • Better understanding of consumer needs and target higher value markets. • Facilitate development of on-line trading platforms, or virtual online cooperatives. • Data analysis can play a significant role in developing new insurance products. • Ultimately, enterprises will use big data because it creates value by solving new problems, as well as • solving existing problems faster or cheaper or providing a better and richer understanding of those problems. **Technological Impact:** Capability of dealing with 5 Vs: • Volume (magnitude of data) • Variety (data from heterogeneous sources), • Velocity (speed of data generation and delivery, which can be processed in batch, real-time, nearly real-time, or streamlines) • Veracity (data quality and level of trust) • Value (detecting underexploited values from big data to support decision-making)
Challenges	**Organizational Challenges:** • Big Data decentralization • Big Data control when there are multiple actors involved • Big Data trust, privacy and security among actors • Big Data Monetization (transfer of rights on data) **Social Challenges:** • Demonstrate value of innovations as compared its costs, to encourage companies and individuals to collect and exchange data • Exploring the ethical implications of Big Data in food and agriculture • Availability of skilled human resources for big data analysis **Technological Challenges:** Improving the capability of dealing with 5V's • Volume (data exponentially increased, posing a challenge to the capacity of storage devices) • Variety (sustainable integrate and combine data from different sources: sensors, Internet of things (IoT), mobile devices, online social networks, in structured, semi-structured, and unstructured formats) • Velocity (real-time data processing) • Veracity (ensure quality and reliability) • Value (provide more value and insights from data) • Valence (support of connectivity in data). The potential of connectivity between systems is being constrained by a lack of common data standards or easy-to-use ontologies. • Combine the three levels of analytics: the performance of prescriptive analytics would heavily rely on those of descriptive and predictive analytics since providing the value of input parameters in the prescriptive model • Combining different data analytic techniques to develop more advanced and adaptive BDA models for DSS • Lack of decision support tools and willingness to share data • New tools and BDA techniques for distributed SC and distributed computation Integration with other technologies • Openness of platforms to accelerate solution development and innovation in general but also empower farmers in their position in supply chains.

Table 4
Artificial Intelligence: Impact and Challenges.

Artificial Intelligence	
References	(Mercy et al., 2011; Liakos et al., 2018; Divya and Sreekumar, 2014; Mishra et al., 2014; Mishra et al., 2016; Elsayed et al., 2018; Reshma and Pillai, 2018)
Impact	**Functional impact:** AI techniques enable: • Classification: to predict the categories of input data for e.g. weather attributes are sunny, windy, rainy etc. • Regression: to predict numeric value e.g. price of stocks. • Clustering: to organize similar items in-to groups. • Association Analysis: to find interesting relationships between sets of variables. • Graph Analysis: to use graphic structure to find connections between entities. • Decision Tree: To predict modelling insights of objective variables by learning simple decision rules inferred from the data features. Above capabilities have been applied to: • Crop Management (yield prediction, disease detection, weed detection, insect pests, biotic stress in crop, crop quality, species recognition, predict soil moisture) • Water management (smart irrigation systems), • Weather forecasting • Soil management • Monitoring faster and with greater accuracy than other monitoring systems • Grading and sorting • Fraud detection system at very high speed, efficiency and with huge scale • Livestock (animal welfare, livestock production) • Environmental Protection • Production Planning **Economic Impact:** • Reduce employee training costs • Create efficiencies, improve problem solutions and reduce the time needed to solve problems. **Social Impact:** • Combine multiple human expert intelligences. • Reduce the amount of human errors. • Review transactions that human experts may overlook. • Reduce human intervention enabling human expert to concentrate on more creative activities **Business Impact:** • Automated decision-making • Expert system increases the probability, frequency and consistency of making good decisions, additive effect of knowledge of many domain experts, facilitates real-time, low-cost expert-level decisions by the non-expert, enhance the utilization of most of the available data • Learning ability Artificial Intelligence, goes a step further by not simply applying pre-programmed decisions, but instead exhibiting some learning capabilities • Data transformation: ML and AI can help create value by providing enterprises with intelligent analysis of big data and capturing structured interpretations of the wide variety of unstructured data increasingly available. **Technological Impact:** • Advancement of ML with machine vision will make agricultural technologies accurate, robust and low cost. • AI can be used to identify and clean dirty data or use dirty data as a means of establishing context knowledge for the data. • AI contributes to the velocity of data, by facilitating rapid computer-based decisions that lead to other decisions • AI contributes to variety mitigation by capturing, structuring, understanding unstructured data generating structure data • AI allows data analysis and decision making • From smart machines to clever computers and to Artificial Intelligence (AI) programs. • Expert systems developed in regional languages to be more accessible
Challenges	**Social Challenges:** • Replacement of human intervention perceived as a threat **Technological Challenges:** • AI to further facilitate additional developments on visualization • AI algorithms designed for single-machine environments might have emergent subproblem structures useful for parallelization. • Adding speech interface to the system may be proved to be more beneficial for the farmers of the remote area • Expert systems will not be able to give the creative responses that human experts can give in unusual circumstances. • Lack of flexibility and ability to adapt to changing environments. • Not being able to recognize when no answer is available. • Knowledge acquisition remains the major bottleneck in applying expert system technology to new domains. • Maintenance and extension of a rule base can be difficult for a relatively large rule base • Enhance IoT with machine learning techniques to analyse data captured by sensors in real time in agriculture.

It is not new that, nowadays, agricultures supply chain practices, especially regarding to food products, are currently under public scrutiny. As established by Van Der Vorst (2006), this is because several factors, which considers food contamination issues, the new consumer healthy requirements, requirements for more precise information about the farming, marketing, and distribution practices used to bring the agricultural products into the shelves into supermarket, to name a few. In this same context, and regarding to Suprem et al. (2013), agricultural industry has been solely dependent on human labour with limited application of mechanical equipment and machines. Moreover, the applications of advanced technology such as embedded computing, robotics, wireless technology, GPS/GIS (Geographical Positioning System/Geographical Information System) and DBMS (Database Management System) software are seen to be recent developments, where regulations are vaguely considered.

Moreover, the increasing gap between farmer's expectations and the ability of the government led extension services has created a big business opportunity for private parties (Kumar and Ali, 2007). In this context, the information about the geometric properties of crops provided by digital based techniques, such as: ultrasound, digital photographic techniques, light sensors, high-resolution

Table 5
Summary of methods and approaches for Agriculture supply chain Decision-making processes (adapted from (Routroy and Behera, 2017)).

Agriculture Supply Chain domain	Recommended Key/relevant Decision-Making methods	Key selected Authors
Risk management	Multi-Criteria decision-Making & Interpretive Structural Modelling, Hazard analysis and critical control points, Chain Traceability Critical Control Points	(Astuti et al., 2013; Olsson and Skjöldebrand, 2008; Opara and Mazaud, 2001)
Collaboration	Supply Chain Collaboration Index, Policymaking	(Bezuidenhout et al., 2012; Kalaitzis et al., 2007)
Governance	Transaction cost economics, vertical integration, product development and diversification	(Zhang and Aramyan, 2009; Dolan and Humphrey, 2000; Chetwood et al., 1997)
Cold chain management	Fuzzy interpretive structural modelling, Structural self-interaction matrix, RFID Technology, Time–temperature data loggers, Microbiological analysis	(Joshi et al., 2009; Kelepouris et al., 2007; Willems et al., 2009)
Globalization	Six T's, surveys, Define–Measure–Analyse–Improve–Control, Inspections	(Robinson and Carson, 2015; Carnahan et al., 2019)
Information and communication technologies	ISO 22000, Radio Frequency Identification, Critical Control Points, Food Traceability System, ITC hubs, Production planning, five-point Likert scale, ANOVA, surveys, ORACLE database management, EDI, iterative design steps a proof of concept, Cordys, IBM Websphere, SAP Netweaver, Microsoft Biztalk, B2B	(Shirani and Demichela, 2015; Kök, 2009; Ali and Kumar, 2011b; Verloop et al., 2009; Ghisi and da Silva, 2001)
Logistics	Two-phase solution approach, Capacity analysis, mixed integer program, multi-objective optimization, two-echelon location–routing problem, Genetic Algorithms, sustainable supply chain network design, multi-objective mixed-integer programming, triple bottom line, Particle swarm optimization, System of Quality Safety Control, ERP Systems, Automated Information Systems, Digital control systems.	(Lamsal et al., 2016; Govindan and Jafarian, 2014; Tan, 2012; Van der Vorst et al., 2005)
Short food supply chain	Policy reports analysis, labelling, Marketing Challenge regulations, resilience analysis, information sharing, vertical integration, interviews,	(Canfora, 2016; Smith et al., 2016; Brown, 2014)
Sustainability of ASC	Conceptual models, Food supply chain economic analysis, labour productivity, data analysis, life cycle assessment,	(Yakovleva, 2007; Del Borghi et al., 2014)

radar images, high-resolution X-ray computed tomography, stereo vision and LIDAR sensors; has innumerable applications in agriculture. Some important agricultural tasks that can benefit from these plant-geometry characterization techniques are the application of pesticides, irrigation, fertilization and crop training, improving the environmental and economic impact. But there is still a need to resolve several technological and commercial questions (Rosell et al., 2012). In line to this, agriculture technologies are focused on how traceability can be performed, in fact, the food industry had developed efficient traceability methods for the management of logistics and warehouses, based on the balance of costs and benefits of the traceability system level (Dabbene et al., 2013).

Because of this, several authors are currently reviewing main agriculture supply chain technology based methods, and example of this is provided by Ahumada and Villalobos (2008), who identified that the use of integrated planning models in the agriculture supply chains is still very limited, with a high potential to manage perishable agri-food products, especially to deal with complex environments. In addition, (Ali and Kumar, 2011a) study the implication of using ICT in agriculture. From the authors' findings it is highly appreciated that there is still a medium level of dissemination of information and knowledge sharing in agricultural developments (Boshkoska et al., 2019), as well as there is still a need for empirical evidences as to how ICT interventions are enabling the farmers to take informed decisions. Complementary to this, S. Araba and M. Fellows (Araba and Fellows, 2009) address that the majority of current research have not established a clear link between public access to ICTs and socioeconomic change/impacts in agriculture. In fact, there is a need for researchers to go beyond anecdotal evidence of downstream public access impacts on end-users. Nevertheless, it is also evidenced that there is still limited ability on information to make definitive statements about agriculture expected impacts, as well as to identify and attribute specific impacts to specific ICT usage. Table 5 presents a summary on well-known methods and approached to support this, in special the agriculture supply chain decision-making methods.

Hence, and as depicted from Table 1, as studied and established by Reardon et al. (2019), the food system can be thought of as "dendritic," linking R&D, finance, input, and output supply chains. This means (1) the first and "core" supply chain, is the output Supply Chain. The second and upstream "feeder" supply chains are the farm input supply chains. The third and downstream 'feeder' supply chains are those supplying inputs to the post-farmgate segments. The fourth "pan-system feeder" supply chain is that supplying finance into every segment of every chain in the dendritic system. The fifth 'feeder' supply chain is a broad set of public assets apart from agricultural research institutions. The sixth set of "feeders" is the R&D supply chains, which supply technology and product innovations. Moreover, the ICT challenges in Agriculture supply chains are still open. Birkel in Birkel and Hartmann (2019), studied most of the recent ICT developments in this field, and found that most of the technological challenges in agriculture mainly includes security issues, lack of standards and interoperability, as well as hardware and software limitations are the focus of current research. Hence, the main challenges and risks are also in relation to the methodology, where (Ben-Daya et al., 2017) has revealed that the design aspect is primarily identified as a technological issue, while neglecting social and political challenges.

Food processing companies' projects must benefit from financial levers that the government makes available to all in the manufacturing sector (Hernández et al., 2020). In order to further stimulate the investments, particularly in the SMEs and in innovative sectors, from financial tools considering the needs of the processing sector are decisive for the development of the implementation of development projects (Hernandez et al., 2020).

In a business environment characterized by technological innovation, the consolidation of industries, deregulation and demand for consumers in constant evolution, the approaches of the traditional managers can no longer allow for companies to remain profitable. They are therefore forced to find new ways to stay competitive in agri-food domain, as it is also the case for all other industrial sectors (Boehlje, 1999; Senge, 1997; Senge et al., 2006).

In the value chain management (VCM) domain, the informed decision making to unite resources to improve the competitiveness, is proving to be a powerful strategic approach that allows organizations to adapt to an environment of business in full motion. (Bonney et al., 2007; Collins, 2011; Dunne, 2008; Fearne, 2007; Fernandez et al., 2019; Liu et al., 2019).

The concept of a continuous observation results in continuous and significant improvement of the design and the system performance, this is only possible when the companies are able to establish a degree of coordination and integration with their suppliers and customers that do not allow them the usual relationships with the latter based on the transactional approach buyer-seller (Sparling, 2007). Closer strategic relationships with customers and suppliers allow companies to better learn and adapt (Cohen and Levinthal, 1990). Multiple firms that co-invent and work together for the same objectives using integrated processes can increase their performance in a much more significant way that if they had gone it alone (Bonney et al., 2007; Fearne, 2007). Co-innovation allows companies to improve their own practices as well as those of all of them, it is a process that gives companies competitive forces that are difficult to match by others (Bonney et al., 2007; Collins, 2011). Several of the cases mentioned below demonstrate the benefits sustainable and competitive products obtained by companies who have chosen to co-innovate with other members of their supply chain.

5. Conclusions, vision and perspectives

For this scientific contribution to knowledge, more than two hundred papers support the analysis on scientific work on the smart agriculture technology trends, but, more importantly, on how they emerge as a main concept in the agriculture domain as Agri-Food 4.0. From this reviews and analysis, it is clearly revealed that integration across new technologies allows smart agriculture to address important farming objectives as water saving, soil conservation, limit carbon emission and productivity increasing by doing more with less. In fact, the new technologies have a positive impact and at the same time pose new challenges in the management of different domains of human knowledge. Hence, two main conceptual pillars impact and challenges, arising from the use of various technologies in the world of the new conception of agriculture are the fundamental aspects in Agri-Food 4.0. A precision is due. This paper focus principally on the factory farm model issued from the "western" style. In those farms, the Agri-Food 4.0 started to be applied and validated. The focus is more specialised on the industrial farming although the Agri-Food 4.0 is started to be adapted also to the organic and silvo-pasture paradigms.

The paper pays attention particularly to four major technologies, the Internet of Things, the Blockchain, the Big data and the Artificial Intelligence. For each of those technologies is presented some type of impacts: functional, economic, environmental, social, related to the business and technological and the challenges that come with their introduction. The literature is segmented in relation to the functionality of the specific technology and a panoramic view gives the possibility to better understand the paths needed to face the new challenges.

The future of the Agriculture domain is in the creation of a resilient and sustainable farming system. On the four types of crop-based uncertainty that have been identified: Product, Process, Market and Environment the core problem is the management. Poor management of these sources of uncertainty have a negative impact on safety, quality, quantity and waste of products as well as human, technological and natural resources. Today, and always more in the future, the data is the lifeblood of any business and the agricultural business is not an exception but rather a referent.

As aforementioned in the discussion section, the new technologies have a great impact on the reduction of uncertainty since they allow obtaining precise data in real time, and real-time information tools provide new opportunities for companies to react more quickly to changing conditions in the supply chain. Our interest in the next future is to use formal methods to extract knowledge from the interrelation of the difference technologies impacts and from the existing solutions to the highlighted challenges to increase the efficiency, sustainability, flexibility, agility, and the resilience along the whole supply chain from the farmers to the final customers, and the analysis and outcomes from this paper, will contribute to support that from the main research knowledge findings.

Declaration of Competing Interest

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