AI Applications of Data Sharing in Agriculture 4.0: A Framework for Role-based Data Access Control

Konstantina Spanaki [a], Erisa Karafili [b], Stella Despoudi [c, d]

[a] School of Business and Economics, Loughborough University Loughborough, United Kingdom

[b] School of Electronics and Computer Science, University of Southampton, Southampton, United Kingdom

[c] School of Economic Sciences, University of Western Macedonia, Grevena, Greece

[d] Aston Business School, Aston University, Birmingham, United Kingdom

Industry 4.0 and the associated IoT and data applications are evolving rapidly and expand in various fields. Industry 4.0 also manifests in the farming sector, where the wave of Agriculture 4.0 provides multiple opportunities for farmers, consumers and the associated stakeholders. Our study presents the concept of Data Sharing Agreements (DSAs) as an essential path and a template for AI applications of data management among various actors. The approach we introduce adopts design science principles and develops role-based access control based on AI techniques. The application is presented through a smart farm scenario while we incrementally explore the data sharing challenges in Agriculture 4.0. Data management and sharing practices should enforce defined contextual policies for access control. The approach could inform policymaking decisions for role-based data management, specifically the data-sharing agreements in the context of Industry 4.0 in broad terms and Agriculture 4.0 in specific.

Keywords: agriculture 4.0; design science; artificial intelligence; data sharing; role-based access control

1 Introduction

The evolution of Industry 4.0 in the agrarian sector, referred to as Agriculture 4.0, introduces multiple opportunities for farming operations. Agriculture 4.0 paradigm presents the evolution of the farming field as data-driven initiatives and applications in various areas (i.e., agriculture) are becoming economically viable (Spanaki, Sivarajah, Fakhimi, Despoudi, & Irani, 2021). The proliferation of data and the associated applications have evolved due to the lower (comparatively to previous years) costs of sensor solutions, data storage and processing in cloud infrastructures, development and expansion of mobile networks and the transmission of data sets from fields around the world (Mikalef, Boura, Lekakos, & Krogstie, 2019). The use of data can improve the practices and operations of individual farms and a large group of farms. Farms can, now more than ever, benefit from the use of information, technology, equipment and a wide range of services (Spanaki, Karafili, Sivarajah, Despoudi, & Irani, 2021). The evolution of agrarian operations should not only focus on value creation for the consumers but also the individual farmer and the society through the use of smart and intelligent services and digital platforms (Spanaki, Karafili, et al., 2021; Spanaki, Sivarajah, et al., 2021).

Applying data-intensive, smart practices and Internet of Things (IoT) technologies in agriculture and farming; can provide a lens for ensuring the transparency of the farming practices and sustainability of the agricultural sector and agrifood production processes. The focus of Agriculture 4.0 on digitalised ways of farming can generate renewed interest in transforming the traditional operations and processes to digital data-intensive ones focusing on analytics and decision-making practices. However, there is still an open discussion and multiple challenges about Agriculture 4.0, specifically a resistance wave from small and medium farms due to data sharing concerns and access control policies of the parties' data (Angelopoulos et al., 2021; Ioannou, Tussyadiah, & Lu, 2020). Building on the background of agricultural operations, the evolution of industry 4.0 and data management, this paper proposes an approach based on formal reasoning from Artificial Intelligence (AI) techniques applied in data access control. The AI approach defines Data Sharing Agreements (DSAs) around specified attributes; proposed to ensure that agricultural data are shared among the interested parties; set as a priority for compliance with the regulatory and policy requirements.

The study follows a design science approach through a smart farm scenario, motivated by the agricultural sector's data-sharing problems. The research aim is to present AI techniques through DSAs as an essential path for data management among various actors of the farming sector. Following the above aim, the paper sets three objectives. The first objective is to enhance the theoretical stream of the agricultural sector and data management in the context of Industry 4.0, focusing on data sharing decisions. As a second objective, the study develops the concept of DSAs, explaining and framing the design approach's scenario for role-based data access control decisions among farming stakeholders by applying AI techniques (argumentation reasoning). The final objective extends the proposed approach for broader AI-driven data management applications in contextual environments, specifically for Industry 4.0, where data sharing challenges occur. The research's ultimate implication is to inform policymaking for data sharing and access control and provide a research agenda for future data sharing contextual AI applications.

Initially, we present the agricultural sector's theoretical background regarding the knowledge and information sharing practices; and extend this background within the context of Agriculture 4.0 and the relevant data management practices. Then, we draw on the methodology of Design Science along with the context of Data Sharing Agreements (DSAs) to explain the research strategy and decisions about the study. Following the research strategy, we develop the proposed approach through a smart farm scenario where we show the practical contributions of the study to data sharing practices and access control decisions in farming operations. Finally, we discuss and explain the implications of the study and future research avenues for Agriculture 4.0 and contextual cases of Industry 4.0.

2 Theoretical Background

Previous research has highlighted a growing desire to adopt digital technologies and Big Data in all industries (Sivarajah, Kamal, Irani, & Weerakkody, 2017), also sweeping through agriculture. The fourth industrial revolution, referred to as Industry 4.0, has also influenced the agricultural sector. As stated by CEMA (CEMA - European Agricultural Machinery, 2017a, p. 1) the *"Digital Farming is structurally similar to the concept of Industry 4.0"*. Nonetheless, the critical distinguishing parameters in agricultural production processes are somewhat different from industrial processes. Agriculture is heavily determined by natural and biological factors (CEMA - European Agricultural Machinery, 2017a, 2017b), and therefore the 'physical' artefact should be strongly considered. The terms' Digital Farming', 'Smart Farming', 'Farming 4.0' and 'Agriculture 4.0' often refer to similar contexts and therefore are used interchangeably (Lamborelle, 2016; Weltzien, 2016; Yahya, 2018). Our study follows the definition of 'Agriculture 4.0' (CEMA - European Agricultural Machinery, 2017a, p. 1) as the 'evolution in agriculture and agricultural engineering from Precision Farming to connected *knowledge-based farm production systems'*. Agriculture 4.0 suggests a data-intensive approach to farming in three ways that are not yet explored in previous studies of the field (Kaloxylos et al., 2012; Pham & Stack, 2018; Wolfert, Ge, Verdouw, & Bogaardt, 2017). The digital transformation appears through a holistic reform of the sector (including practices and processes), changes in roles and relationships of the actors and variations of the technology and tools used for the farming field. As the context of Agriculture 4.0 infers to a digital transformation of the agricultural sector (the processes, actors, and relationships), the background and the strong linkages to Supply Chain Management (SCM) and Artificial Intelligence (AI) should not be neglected. The paradigm of Agriculture 4.0 sets the technology and data aspects in the core of attention and examines the processes, actors and relationships in contextual environments (agricultural context).

The study herein primarily draws on the contextual background of the agricultural sector regarding the knowledge and information sharing practices; and extends this background within the context of 'smart farming', 'Agriculture 4.0' and the relevant AI-enabled data management practices. The agricultural background informs the case specifics, and the associated conditions and AI enables the development of the techniques proposed; therefore, the consideration and links of these theoretical streams will be presented in this section.

2.1 The Agricultural Sector

The Agrifood supply chains and agricultural sector encompass a set of activities that move agricultural products from production to consumption; the set of operations includes farming, processing, packaging, warehousing, transportation, distribution, marketing, and sales (Iakovou, Vlachos, Achillas, & Anastasiadis, 2014). Several stakeholders act as part of these activities, such as research institutions, farmers, agricultural cooperatives, intermediaries, manufacturers, distributors, traders, wholesalers, retailers, and consumers (Jaffee, Siegel, & Andrews, 2008). Except for the agricultural actors, there are different stakeholders, i.e., primary and secondary stakeholder groups that influence business operations (Clarkson, 1995). Primary stakeholder groups are vital for the sector's existence, while the secondary stakeholders' actions may have a low impact on the business operations (Bremmers et al. 2007). Some examples of agricultural stakeholders are Non-Governmental Organisations (NGOs), governments, statistical institutes, international organisations, companies' vendors, other agricultural companies' competitors (World Bank 2010). Stakeholder interactions enable firms to interact with each other in order to learn, negotiate, set standards, and make future plans (Glasbergen 2007; Braziotis et al. 2013).

The agricultural sector is highly concentrated on retailers, large agricultural enterprises and small scale farms (UNCTAD, 2016). Farmers face many challenges due to high input costs, production inefficiencies, high levels of food waste, and low-profit margins (Papaioannou, Mohammed, Despoudi, Saridakis, & Papadopoulos, 2020). All the different agricultural stakeholders are also affected by the sector-specific challenges related to the increasing need for transparency and sustainability, world's food insecurity, future resource scarcity, limited agricultural land availability, food waste levels across the chain, and supply chain risks (Driscoll, 2012; UN Food and Agriculture Organization, 2011).

The production and the output of the agricultural sector compared to other food supply chains and networks (Tsolakis, Keramydas, Toka, Aidonis, & Iakovou, 2014) has some unique characteristics as short shelf-life, seasonality, quality and quantity variability, compliance with national and international food regulations, specific requirements for transport, handling, and storage due to perishability, need for efficiency and productivity, price variability, dependence on weather conditions (Iakovou et al., 2014; Zissis, Aktas, & Bourlakis, 2017).

2.2 AI for Data Management in contextual environments

Nowadays, various sectors, as a result of information sharing practices, are increasing investments in data-driven decision-making and business analytics solutions for improving their performance and operations (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Feki, Boughzala, & Wamba, 2016; Mikalef et al., 2019; Wamba, Akter, Coltman, & Ngai, 2015). The use of data in organisations of various fields is presented in the last decade as a solution for enterprises to create value by using their analytical skills in visualising, optimising and transforming their operations and innovation potentialities (Hughes et al., 2020; Kumar et al., 2020; Mikalef, Boura, Lekakos, & Krogstie, 2020; Papadopoulos, Singh, Spanaki, Gunasekaran, & Dubey, 2021; Pappas, Mikalef, Giannakos, Krogstie, & Lekakos, 2018; Shareef et al., 2021). Artificial Intelligence (AI) in our study refers to *cognitive processes and especially to reasoning* (Pomerol, 1997, p. 3) and will be applied in our study as the basis of techniques proposed for data sharing and access control. As it is also explained in the study by Spanaki et al. (2021, p. 4), *AI applies human problem-solving behaviour and skills in complex real-world tasks*, can be the basis to develop various techniques, as a conceptualisation, but also as increasing the capabilities and skills for improved firm performance (Mikalef & Gupta, 2021). As data governance and innovation through data (Christiaanse, Diepen, & Damsgaard, 2004; Mikalef, Boura, et al., 2020) in the agricultural context is one of the major challenges in agricultural platforms, AI techniques can provide a way to solve such problems through multidisciplinary approaches (Duan, Edwards, & Dwivedi, 2019; Dwivedi et al., 2021; Spanaki, Karafili, et al., 2021).

The topic of data management as a strategic way in developing efficiencies at tactical and operational levels (Wang, Gunasekaran, Ngai, & Papadopoulos, 2016), as well as information and data sharing, implies the requirement for data quality evaluation (Hazen, Boone, Ezell, & Jones-Farmer, 2014) in order to control information and data sharing practices. The data quality framing presented in data management literature of the previous decades could be applied in the context of data processing and production (Hazen et al., 2014; Jones-Farmer, Ezell, &

Hazen, 2014; Yeganeh, Sadiq, & Sharaf, 2014). Also, in terms of information sharing and data governance, there are various recent discussions as those of Tallon et al. (2013) and Tallon (2013) framing different aspects of data governance, while the empirical work of Mikalef et al. (2020) shows the value of adopting such practices. The primary concern, though, is that it should be extended in a boundary-less context between firms, and the target should be innovative outputs, as these are mostly the results of the data evolution (Popovič, Hackney, Coelho, & Jaklič, 2014; Spanaki, Gürgüç, Adams, & Mulligan, 2018). Nowadays, there are multiple calls for novel techniques in the data-intensive era, focusing not solely on the data processing mechanisms per se but also on the quality and sharing attributes associated with them (Karafili, Spanaki, & Lupu, 2018b).

Data sharing control was not the major focus of data management in previous decades as the data were mostly shared within the boundaries of a company or between single databases (Angelopoulos et al., 2021; Angelopoulos, McAuley, Merali, Mortier, & Price, 2016). Dealing with a sole database or a single company implies that the trust and security issues were solved by the individual sharing entities and the associated agreements between interested parties. Urged by the need to define specific sharing agreements for the data exchanges, the study presents the concept of Data Sharing Agreements (DSAs), which will be developed in detail through the example case.

Our study focuses on the characteristics and aspects of the data (as timeliness, accuracy, etc.) to define the context and governance of data sharing and control practices (Hazen et al., 2014; Jones-Farmer et al., 2014; Yeganeh et al., 2014). Data access control can also base the sustainability of smart farming and overall, the agricultural sector, especially for small and medium farms. With the view on the control of data sharing practices, the concept of DSAs will be adopted for the development of the smart farm scenario and will be further analysed through the example. The basic concepts around the farming context coupled with the agricultural background informed the development of the smart farm scenario, which will be explained in detail in the following sections.

2.3 AI-enabled Data Sharing and the Role-Based Access Control Framework

The application of AI techniques for addressing data sharing challenges can represent human thinking and decision-making through formalism, like argumentation reasoning (Kowalski, 2011; Otjacques, Hitzelberger, & Feltz, 2007). The proposed framework applies preference-based argumentation, nonmonotonic logic, and abductive logic programming for data sharing decisions. The result is represented using a policy language that provides the rules that compose the Data Sharing Agreements (DSA). DSAs define in advance specific rules between the data subject, controller and professor about how the data will be used, collected and shared (Swarup, Seligman, & Rosenthal, 2006). The DSAs also describe the compliance of the different sector rules and regulatory frameworks for data sharing (Karafili & Lupu, 2017; Matteucci, Petrocchi, & Sbodio, 2010). The DSAs are heterogeneous, and therefore, they present various conflicts, especially between legal and business or user requirements. Thus, the DSAs require expressive language to represent the agreements (Karafili & Lupu, 2017; Karafili, Spanaki, & Lupu, 2018a; Karafili et al., 2018b). The studies of DSAs propose a policy language based on logic programming that represents complex agreements and an analysis process for capturing the conflicts and the associated solutions. The main structure of DSAs, as presented in Table 1, requires already defined (a) actors and roles, as well as (b) the variations of the data categories (data management aspects), so as rules and conditions can be formed for the DSAs (Karafili & Lupu, 2017; Karafili et al., 2018a, 2018b).

<table>
<tr><th></th><th>Aspects of DSAs</th><th>Background</th><th>Research Decisions</th></tr>
<tr><td rowspan="2">Pre-requisites</td><td>Actors and Relationships</td><td>Informed by the background of the agricultural sector</td><td>Who is involved, and what information is required to conduct activities?
Role-based decisions based on the agricultural background specifics</td></tr>
<tr><td>Data Categories</td><td>Defined by the agricultural sector specifics and data management background</td><td>How to develop data management rules based on data features?
Agricultural sector context and data management aspects informing the conditions of the AI techniques</td></tr>
</table>

Outcome	**Rules and Conditions**	Policy language (Access Control techniques) for representing rules and conditions. Argumentation and abductive reasoning techniques (techniques from AI) for identifying the correct rules/conditions of application.	*Who can access and what data?* Practical and policymaking decisions relevant to the roles of the actors and the aspects of data

Table 1: Role-based data access control framework

The role-based data access control framework serves as a template (design) for the demonstration of AI techniques based on abductive (Kakas, Kowalski, & Toni, 1992) and argumentation reasoning (Bondarenko, Dung, Kowalski, & Toni, 1997; Dung, 1995) for decision-making mechanisms under conflicting knowledge. Argumentation reasoning permits to represent through the policy language the various conflicting rules, the context where they are valid and the preferences between them. The used policy language comes with its policy analysis based on an abductive constraint logic programming system, A-system (Kakas et al., 2001). In particular, the policy analysis identifies conflicts between policies and resolves them by using the preferences between rules, called priority rules, and explicitly specifying when a rule has to be considered stronger compared to another one. Conflicting rules are rules with conflicting outputs, e.g., one rule is permitting/obliging an action, while another rule is denying the same action. A priority relation, denoted by >, is used to indicate preferences between rules. Given two conflicting rules r_1 and r_2, where for the context and the information available, r_1 should be applied instead of r_2, it is denoted with $r_1 > r_2$.. The policy analysis composes the decision-making mechanism that captures the conflicting rules and decides the DSAs that should apply. The analysis uses a visual tool (GorgiasB) for preference-based argumentation which can be applied to identify conflicting knowledge (Spanoudakis, Constantinou, Koumi, & Kakas, 2017; Spanoudakis, Kakas, & Moraitis, 2017).

3 Research Strategy

Based on a problem-oriented approach, the study is structured using the design science research paradigm based on a smart farm scenario from the agricultural data sharing context. As design science focuses on better understanding how operations can be structured to contribute to the design of systems (O'Keefe 2014), the data-sharing challenges are presented through a framework (design) as a template for applying the data sharing conditions. The framework proposed in this study follows a problem-oriented approach and tries to generate impacts on practice and policy (van Aken, 2005; van Aken, Chandrasekaran, & Halman, 2016), and therefore the target is the impact and not solely knowledge generation (Holmström, Ketokivi, & Hameri, 2009; van Aken, 2005). Design science approaches pose a representation of how the proposed solution to a specific problem could be enacted in practice (O'Keefe 2014; Hevner and Chatterjee 2010; Hevner et al. 2004); therefore, the problem and solution are demonstrated through a smart farm scenario. As in previous studies of agricultural problems (e.g. Irani et al., 2018; Spanaki, Karafili, et al., 2021), design science principles (O'Keefe, 2014) are also informed by the established design science background (Gregor & Hevner, 2011; Hevner & Chatterjee, 2010; Hevner et al., 2004; Peffers, Tuunanen, Rothenberger, & Chatterjee, 2008). The research strategy of this study followed four stages:

- **Stage 1:** Identify the problem of the agricultural sector within the data sharing practices and the objectives of the proposed solution.
- **Stage 2:** Propose the DSA as a template for designing data sharing practices and access control and apply AI techniques, with argumentation reasoning and a policy language to iterate the design through the development phase.
- **Stage 3:** Explain the design through a scenario of the agricultural context (demonstration).
- **Stage 4:** Discuss the use, implications, and future applications of the proposed approach.

The unit of analysis of this study is the smart farm, focusing on the data-sharing challenges, associated decisions and the contextual specifics drawn from agricultural operations. Hence, the particulars of the study will unfold through a smart farm scenario. The scenario is built to incrementally explore the field's empirical inquiry with the case of smart farms scoped around the theoretical foundations of the agricultural sector and the background of information data sharing. The case example supports the research by identifying and familiarising with the context of smart farms (actors, relationships, data, access control, etc.) and Agriculture 4.0 and specifically on the data sharing decisions. The research strategy primarily focuses on understanding the behaviour and choices of the stakeholders involved in the smart farm's showcase scenario and resolve conflicts of interest in data sharing decisions. Therefore, the role-based access control framework provides the basis to incrementally show how role-based access control and data sharing decisions can be defined through the smart farm scenario.

In the smart farm scenario, a policy language is used to model the data access rules, and AI techniques, i.e., abduction and argumentation reasoning, are used during the reasoning and analysis process (Kakas et al., 2001).

4 Analysis of the Smart Farm Scenario

In this section, in order to show the use of the DSAs and the above-introduced framework, we present the case of smart farms within the context of Agriculture 4.0, where there is a process of collecting, processing and sharing agricultural data.

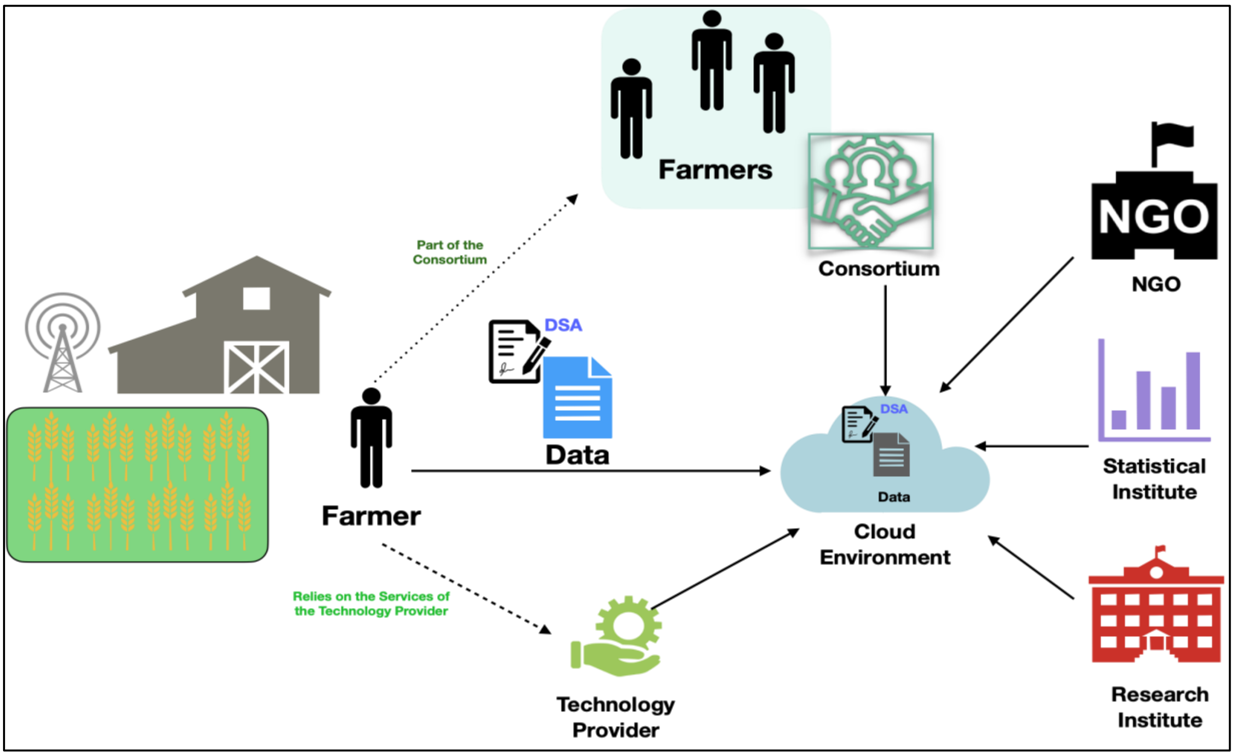

Figure 1: An overview of the Smart Farm Scenario

An overview of this scenario with the various entities involved is provided in Figure 1. The proposed methodology is applied at a high level for the natural representation of the decision-making process and conflict resolution. The representation involves the requirements of the interested actors. The applied framework will represent, build, and enforce the access control policies and priorities of the rules associated with the agrarian field data that compose the DSAs.

4.1.1 Actors and Relationships

The main actor in the example case is the *farmer*, whom we assume is the owner of the agricultural activity and performs the various operations and collects the data. For this case study, the farmer is the *data owner* as s/he is the entity that collects, uses, shares the data. The farmer is also considered the *data subject*, as the various actions are made on her/his data, e.g., her/his personal data, which are part of the agriculture activity data. The data owner can also be the *data controller*, as s/he defines the purpose and means of processing it. Sometimes the farmer relies on third parties that provide the technical support for collecting the data. In this case, the farmer, who is the *data owner/subject*, is not the data controller, as s/he delegated the control of her/his activity data to a third party that is now the data controller. In case the farmer is part of a consortium that provides help in the digitalisation process, then the farmer can be the data subject but not the data owner.

The *data recipients* are the stakeholders involved in the data sharing process, the acquisition and access of the data, and need to comply with the data controller rules. The data recipients can be research centres, national and international statistics institutes, NGOs (e.g., UN), companies that provide service and technology for agriculture, and other farming activities. The reference farming activity can be part of similar *collaborative* agricultural supply chain operations. These activities are to exchange information, knowledge, technology and commonly sell agricultural products. In this case, the members of the collaboration are also considered as data recipients.

The *data processor* is an entity (public authority, agency, legal person) processing the data on behalf of the data controller. In our use case, the collected/processed/shared data can be stored in the cloud. Thus, the cloud provider is considered the data processor as far as it respects the controller's instructions. The controller rules should be respected by the processor and can also have a legal nature, e.g., if the controller is in an EU country, the cloud provider should as well be in an EU country and cannot share the data with countries outside the EU and EEA.

A *third party* is an entity (public authority, agency, legal person) that is not the data subject, data controller or processor and is under the data controller's direct authority or processor. In our case, a company outside the collaboration, which is granted access, can be considered a third party. Once access is obtained, the third party becomes a data controller and has to comply with the data protection principals.

The data collection is performed either manually or through technological applications (IoT devices, drones, etc.). The data collection process is highly related to the accuracy and transparency of the data quality; for example, there are data collected manually more or less accurate compared to the data collected by a device due to the efficiency or the reliability of the process steps. The data collection is also directly linked to the timeliness, as it can occur at various time intervals, e.g., every hour/day/month or a continuous collection. The collection time/period influences the timeliness of the data. The timeliness aspect of the data is strictly related to their type, e.g., data collected in the last 3 hours for the humidity of the air are following a different *timeliness* level than the data collected 1 week ago, while the timeliness level of the composition of the soil data collected 3 hours or 1 week ago is similar because it takes a more extended period of time for this type of data to have meaningful changes.

4.1.2 Categorisation of the Data

The stakeholders/ actors might have conflicting interest with each other. The main actors are the *owners* of the agricultural activity represented by $\mathcal{O} = \{O_1, O_2, \dots\}$. The data consumers follow different patterns and can be identified through a segmentation analysis of who may be interested in this kind of data (which is out of the scope of this study). In our case, we consider only as data consumers the *research institutes* $\mathcal{R} = \{R_1, R_2, \dots\}$, *statistical institutes* $\mathcal{S} = \{S_1, S_2, \dots\}$, *international non-governmental organisations* (NGOs) $\mathcal{H} = \{H_1, H_2, \dots\}$, *companies-vendors that provide agricultural services and technology* $\mathcal{ST} = \{T_1, T_2, \dots\}$. As described previously, the activities can be part of an agricultural collaboration, also called *consortium* that we can denote as $Cons$. In case the activities are part of the same collaboration (e.g., two activities O_1, O_2 are part of the same consortium, denoted as $Cons(O_1, O_2)$) they have collaborative relationships with each other, and they do not consider their collaborators as immediate competitors.

We divide the dataset of the example case into five different types that represent the type of data and their privacy level:

- private data: *Priv*(*data*), e.g., owner's private information, contacts.
- administrative data: *Admin*(*data*), e.g., income, taxations, main agricultural activity.
- product data: *Prod*(*data*), e.g., production-related data, production lines, seasonal production.
- innovation data: *Innov*(*data*), e.g., novel techniques, processes, production mix, patents, licensing, innovation uniqueness of the activity.

- sensitive data: *Sens*(*data*), these data are part of the production data but are sensitive for a successful production, e.g., methods of using specific fertilisers.

Considering data collected within specific timeliness and following accurate processes, we can perform an *alteration mechanism* able to degrade the timeliness and accuracy of the data. Thus, given the original data that are considered of high accuracy and timeliness, we can tailor altered versions of the data with lower accuracy and timeliness. The alteration of the data permits us to provide different access levels to the data to different actors according to their role (role-based access control). The alteration predicates[1] are given below, where the first predicate alters the accuracy of the data from high to low, while the second predicate modifies the data timeliness from high to low. The first parameter of the predicate is the input data, while the second one is the output data.

$$Alter\_Accuracy(High\_Data, Low\_Data)$$

$$Alter\_Timeliness(High\_Data, Low\_Data)$$

The owner's data are used, accessed, and shared between different entities by respecting their DSAs. The first step is to agree on the terms of the DSAs, where some DSAs terms, usually legal ones, are irrefutable. The DSA rules are represented using a policy analysis language that is an enhanced version of the language presented in (Karafili & Lupu, 2017; Karafili et al., 2018a, 2018b). For the sake of simplicity, in this paper, we do not present the DSAs rules with the policy language, but we use a semi-natural language. Thus, the predicate from the policy language

$$permitted/denied(Subject, Target, Action, Time)$$

is transformed into

$$Action(Target, Subject, permitted/denied).$$

The above predicate $permitted/denied(Subject, Target, Action, Time)$ means that a particular *Subject* is *permitted/denied* performing a particular *Action* at the instant of *time* to the *Target*. The actions can be of various type (e.g., read, delete, share, etc.).

The predicates like $holdsAt(predicate(Subject, Target), Time)$ are transformed into $predicate(Subject, Target)$, where $holdsAt(predicate(Subject, Target), Time)$ means that a particular predicate is true at the instance of time defined by the input Time. The predicate

[1] The predicate is stated here as a function. This function either provides an output, given a particular input, or provides a relation that holds between the provided pieces of input.

deals with a Subject and Target, e.g., $\mathrm{owner}(\mathrm{Rob}, \mathrm{A\_Soil\_data})$ states that Rob is the owner of A_Soil_data.

4.1.3 Role-based Access Control: Rules and Conditions

The following analysis provides the *conditions* that describe how the data access/sharing should be made for different users and the associated rules that specify each proposed role-based access control decision. We analyse the presented rules using an automatic analysis tool for preference-based argumentation and abductive reasoning to identify conflicting knowledge (Spanoudakis, Constantinou, et al., 2017; Spanoudakis, Kakas, et al., 2017). The identified conflicts are solved by introducing priorities in the order of application of the rules.

Condition 1: The farmer is the owner of the data and can access the data.

Rule 1: The data owner can access his/her data with the original quality they were captured.

$$(1) \quad Access(data, O, permitted) \leftarrow Owner(O, data).$$

The conclusion of the rule is presented on the left side of the arrow (←) in this case is $Access(data, O, permitted)$, which states that subject O is permitted access to the data. The preconditions of the rule are presented on the right side of the arrow (←). In the above case, the precondition of the rule is composed of just one predicate that needs to be satisfied in order to have the conclusion. The precondition is $Owner(O, data)$, which means that subject O needs to be the owner of the data. In case there is more than one predicate to be satisfied, then the predicates are separated by a comma (,) in case they all need to be satisfied for the conclusion to hold, or by a (∨) that represent the logical symbol for OR, in the case at least one of the predicates needs to be satisfied in order for the conclusion to hold. In case the conclusion is always true; thus, it does not need any precondition to hold, then the right side of the arrow is empty.

Condition 2: Research Institutes can provide tailored services and information about agricultural production, advances in technology (Agri-Tech) and advice on farming practices and activities.

Rule 2: The research institute can access all the data related to a particular product, and the accuracy and timeliness of the data are high.

The research institute (R) can access all the related data of a particular product that they are interested in (*Interest(R, data)*), and the data are only the production-related data (*Prod(data)*). In this case, as the subject is a research institute $ResearchI$ (R), and its main focus is to conduct scientific research that in the future would bring benefits to the farmer, R can access the data, and the quality of the data is not altered.

$$(2)\quad Access(data, R, permitted) \leftarrow Interest(R, data), ResearchI(R), Prod(data).$$

Condition 3: NGOs can access a tailored dataset about product-related data, e.g., production rates.

Rule 3: The NGOs can access only the product-related data with low accuracy and timeliness. The NGO's can access only production data with low accuracy and low timeliness because they do not need detailed data. In this case, it is given access to all production data, which are altered. When doing the alteration, starting from the production data, which we denote by $data'$, we first make a restriction/alteration of the timeliness, the result is denoted by $data''$, and then perform an accuracy alteration on $data''$, where the result is denoted by $data$, as shown below. An entity (H) is considered an NGO when it has humanitarian purposes, denoted by $Humanitarian(H)$.

$$\begin{aligned}(3)\quad Access(data, H, permitted) \leftarrow\ & Prod(data'), Humanitarian(H),\\ & Alter\_Timeliness(data', data''),\\ & Alter\_Accuracy(data'', data).\end{aligned}$$

Condition 4: Statistics institutes can access a tailored dataset about product-related data, e.g., the production rates.

Rule 4: Statistics institutes can access product-related and administrative data with low accuracy.

When it comes to statistics institutes, denoted as $Statistics(S)$ both the production-related and administrative data are shared with low accuracy.

$$\begin{aligned}(4)\quad Access(data, S, permitted) \leftarrow\ & \big(Prod(data') \vee Admin(data')\big),\\ & Statistics(S), Alter\_Accuracy(data', data)\end{aligned}$$

In case the statistics institute is an international one, then there is an exception for the above rule. In this case, the data provided to the international statistics institute will be of low timeliness, e.g., not recent or real-time.

Condition 4a&b: International statistics institutes can have a high-level view of the data (low accuracy and low timeliness).

Two additional rules are applied for data sharing and access for the international statistics institutes. The first rule (4a) states that rule (4) is not applicable in the case of international institutes, while rule (4b) indicates the exception of rule (4a).

Rule 4a: International statistics institutes cannot access the production-related and administrative data with low accuracy.

(4a) $Access(data, S, denied) \leftarrow (Prod(data') \vee Admin(data')), Statistics(S),$
$Alter\_Accuracy(data', data), Owner(O, data'),$
$Location(O, N_1), Location(S, N_2), N_1 \neq N_2.$

In the above rule, we check if an entity is national or international by checking the location. In particular, if the location (that provides the country) of the entity is the same as the one of the data owner that it is a national; otherwise, if the locations are different ($N_1 \neq N_2$), then this entity is an international one.

Rule 4b: International statistics institutes can access the production-related and administrative data with low accuracy and low timeliness.

(4b) $Access(data, S, permitted) \leftarrow (Prod(data') \vee Admin(data')),$
$Statistics(S), Alter\_Timeliness(data', data''),$
$Alter\_Accuracy(data'', data), Owner(O, data'),$
$Location(O, N_1), Location(S, N_2), N_1 \neq N_2.$

The location predicate plays a vital role for the above rules, as it permits to determine if the institute is a national or international one. The location predicate $Location(Sub, N)$ gives the location of the subject in terms of countries. In the above rules, we compare the countries of the institute and the country of the smart farm (where the agricultural activity is performed). The international statistics institute cannot access the latest version of the data even if the data has low accuracy represented by rule (4a), but only to data where their timeliness and accuracy are low represented by rule (4b). Our analysis detects that rules (4) and (4a) are in conflict, and we decide that rule (4a) is stronger than rule (4), denoted by (4a)>(4), in case the institute is an international one. Rules (4a) and (4b) are in conflict with each other, and the performed analysis over the rules detects this conflict. In this case, we decide that rule (4b) has priority over rule (4a), denoted by (4b) >(4a), in case the data has low accuracy and timeliness.

Suppose now that the smart farm decides to share part of the data with other companies that are from the service and technology $S\&T$ agriculture sector. In this case, we give below the rule that describes how service and technology companies should access the data.

Condition 5: Service and technology companies of the agricultural sector can have a high-level view of the data (low accuracy and timeliness).

Rule 5: The service and technology companies can access only production-related data with low accuracy and low timeliness.

The smart farm provides low accuracy and low timeliness data to avoid revealing sensitive and administrative information because the data will be used by S&T companies that can indirectly expose the data to the competitors who also use the service of the same $S\&T$ company.

$$(5)\quad Access(data, S, permitted) \leftarrow Prod(data'), S\&T(S), Alter\_Timeliness(data', data''), Alter\_Accuracy(data'', data).$$

For the above case, when the *S&T* company creates a particular relationship with the smart farm, e.g., the creation of tailored products, providing the technology for collecting/processing/storing the data, then this company can access to the production-related data as well as the sensitive one with high accuracy and timeliness. For simplicity, we call this type of relation *partnership*. Hence, all *S&T* companies that have a partnership relation, denoted by $Partners$, with the data owner can access sensitive and production-related data.

Condition5a: If service and technology companies are direct providers/vendors of technology for the smart farm, they can access the original version of the collected data.

Rule 5a: Service and technology companies in partnership with the smart farm can access production-related and sensitive data without any alteration in accuracy and timeliness.

$$(5a)\quad Access(data, S, permitted) \leftarrow (Prod(data) \vee Sens(data)), S\&T(S), Owner(O, data), Partners(O, S).$$

Usually, other smart agricultural farms, *Agric*, are seen as direct competitors. Therefore, no access to the data of the other smart farms is given to those companies.

Condition 6: Other smart farms competitors of the data subject should not access their competitors' data.

Rule 6: Other agriculture companies have no access to any type of data.

$$(6)\quad Access(data, C, denied) \leftarrow Agric(C).$$

Agriculture companies can be part of a consortium, usually formed as collaboration. Companies (organisations, farmers, etc.) consisting of an alliance or collaboration group are located geographically nearby, or produce the same/similar products, or follow the same/similar production procedures. We denote with *Cons* the relation between two smart farms that are part of the same consortium/collaboration. In this case, as the smart farms, *Agric* do not identify each other as direct competitors, but as associates/allies, they share production-related data with high accuracy and timeliness. Sharing data of low accuracy and timeliness inside the consortium does not provide any benefit, as the smart farms usually are geographically nearby to each other. Therefore, the members of the consortium can have the same data and can verify their accuracy.

Condition 7: Data sharing among farms of the same consortium can bring multiple benefits for the whole collaborative agricultural supply chain. Therefore, they should share the data.

Rule 7: Smart farms that are part of the same collaboration share production-related data.

(7) $Access(data, C, permitted) \leftarrow Prod(data), Agric(C), Owner(O), Cons(O, C).$

Our analysis captures the conflict between rule (7) and rule (6). The decision for this conflict is that rule (7) has priority over rule (6), denoted as (7)>(6), in case the two farms are part of the same consortium; otherwise, the access is not granted.

Often the agricultural supply chains can be affected by natural catastrophes/disasters as well as extremely adverse weather conditions or product diseases. These events are considered *emergency* situations for the smart farm as there are high risks of significant economic losses.

Condition 7a: In case of an emergency, smart farms part of the same collaboration also share sensitive data, as these data can help in creating effective prevention and mitigation measures for the whole collaboration, as well as putting in place aid measures for the affected companies.

Rule 7a: In case of an emergency $Emerg$ the agriculture companies that are part of the same collaboration share production-related and sensitive data.

$$\text{(7a)} \quad Access(data, C, permitted) \leftarrow \big(Prod(data) \vee Sens(data)\big), Agric(C), Owner(O), Cons(O, C), Emerg(O).$$

The policy analysis captures the contradiction between rule (7a) and rule (6), where in case of an emergency and collaboration, it is granted the access to the data, which is denoted as (7a) > (6).

Condition 8: Other entities outside of the previously mentioned cannot warrant access to the data.

Rule 8: Nobody else can access the data.

$$\text{(8)} \quad Access(data, S, denied) \leftarrow .$$

The above rule represents the used criteria "*deny by default*". For activating the above rules, we define that all the above rules (except for rules (4a) and (6) that are not in conflict with the rule (8)) are stronger than rule (8). Thus, in case one of the above rules applies, we give priority to them. Otherwise, access is denied.

The private and innovation data are never shared with other entities. A future ambition could be to understand how to ensure the non-revelation of the innovation data. The revelation can occur by sharing non-innovation data (e.g., production-related or sensitive data) that are linked/related to the innovation ones. The previous incident brings the data owner to expose part of her/his innovation data involuntarily.

The above rules are analysed automatically by our analysis tool, which identifies the various conflictual rules, provides the preference between them or introduce the preferences provided by the tool user, and it gives as a result the rules in the form of access control policies that compose the DSAs.

5 Discussion

The study herein primarily draws on the context of Industry 4.0 and information sharing practices; and extends it with the contexts of 'smart farming', 'Agriculture 4.0' and the relevant data sharing practices. The background of the agricultural sector informs the abductive case study specifics and the associated rules and conditions.

The agricultural sector encompasses a set of activities that move agricultural products across the agrifood supply chain from production to consumption; the set of operations includes farming, processing, packaging, warehousing, transportation, distribution, marketing (Iakovou et al., 2014). A number of actors are involved as part of the interplay of agrarian activities, such as research institutions, farmers, agricultural cooperatives, intermediaries, manufacturers, distributors, traders, wholesalers, retailers, and consumers (Jaffee et al., 2008). The agricultural sector compared to other sectors and, in general, other supply chain networks (Tsolakis et al., 2014), has strong links with the sustainable development goals (SDGs) and specifically food security. In combination with the challenges the stakeholders face, the unique sectorial characteristics can challenge the effectiveness, profitability, and sustainability of the practices and, therefore, provide ground for innovation in the field if technological advances are in place to support these activities (Meola, 2016).

The evolution of Agriculture 4.0 due to the sectoral characteristics and challenges led stakeholders towards more integrated supply chains (Matopoulos, Vlachopoulou, Manthou, & Manos, 2007) and forming strategic relationships collaborations (Daugherty, 2011). Farmer cooperatives and consortiums were established as a first effort to increase the profit margins of farmers and achieve economies of scale by reducing operating and logistics costs and increasing farmers bargaining power (Prahinski & Benton, 2004). Collaboration can be defined as working jointly to bring resources into a required relationship to achieve effective operations in harmony with the strategies and objectives of the parties involved, thus resulting in mutual benefit. Cao et al. (2010) refer to collaboration as a set of interconnected activities that include information sharing, goal congruence, decision synchronisation, incentive alignment, resource sharing, joint knowledge creation, and collaborative communication. Meola (2016) emphasises agricultural collaboration and data-sharing practices as an inevitable step to ensure sustainability and the future of farming practices.

Better and closer collaboration can bring many benefits to farming actors, such as reduced food waste levels, improved performance, and creation of competitive advantage (Despoudi, Papaioannou, Saridakis, & Dani, 2018; Manzini & Accorsi, 2013; Mena, Adenso-Diaz, & Yurt, 2011). For example, creating a competitive advantage through learning alliances' resources, sharing information and knowledge, networks and making joint strategic and trading decisions can result in reduced food waste levels. Additionally, increased levels of collaboration in the farming systems can improve product quality, the efficiency of operations, reduce costs, and increase overall agrifood sustainability (Ji, Jia, & Xu, 2018; Soosay, Hyland, & Ferrer, 2008). Information sharing is seen as an essential element of collaboration that can lead to many benefits such as cost reduction and competitive advantage (Sheu, Yen, & Chae, 2006). Agricultural partners can exploit and complement each other capabilities and resources to achieve the benefits of collaboration (Pretty, 2008). Knowledge exchange and knowledge sharing is another crucial element for successful collaboration, as the actors need to exchange their knowledge regarding food regulations such as food safety and food quality regulations (UN Food and Agriculture Organization, 2017). Therefore we provide here some points that warrant further discussion from the above scenario of the smart farm are the following:

Actors and Relationships: The evolution of Agriculture 4.0 due to the sectoral characteristics and challenges led agricultural stakeholders towards strategic relationships and collaborations (Daugherty, 2011) through digital platforms where data can be shared among various parties. While Cao et al. (2010) refer to collaboration as a set of interconnected activities that include information sharing, joint knowledge creation, and collaborative communication, there are indeed challenges in using digital platforms for collaboration. Collaboration in the agricultural sector can be achieved in different ways from the various stakeholder groups (actors) such as NGO's, research institutes, statistical institutes, and vendors. Meola (2016) emphasises agricultural collaboration and data-sharing practices as an inevitable step to ensure sustainability and the future of farming practices. Information sharing is seen as an essential element of collaboration that can lead to many benefits, such as cost reduction and competitive advantage (Min et al., 2005; Sheu et al., 2006). Effective information sharing in the agricultural sector is critical as it is an exceptional industry with time-critical, high-risk, high control and security requirements as well as demand on supply chain integration (Fiala, 2005). Information sharing in Agriculture 4.0 is seen as key in order to enable supply chain entities to manage unanticipated weather changes, water shortages, product perishability, price volatility and isolation of producers from markets (Barmpounakis et al., 2015).

Categorisation of the Data: Within the context of Agriculture 4.0, the information sharing practices emphasise the use of data and technology in the cyber-physical farm management cycle recently, with a strong focus on data-intensive, informed decisions for the agricultural practices (Kaloxylos et al., 2012; Nukala et al., 2016; Wolfert et al., 2017). The agrarian data and linked data, metadata, information, and knowledge could be vast and can include anything associated with them. Examples could include yield monitoring data (crop yield by time and distance, distance and bushels per load, number of loads and fields), spatial coordinates (mapping fields), fertilisation management data, data from mapping weeds, variable spraying data, topographic data, salinity data, field assessment data, pertinent data, images, geospatial data etc. (Kamilaris, Kartakoullis, & Prenafeta-Boldú, 2017). The volume of this list is enormous and unlimited and is continuously expanding as more technological developments arise. The volume of the data could sometimes hinder the progress and confuse the processes if it is not handled with the required capabilities. The capabilities require advanced intellectual and technical resources to capture, store, distribute, manage and analyse the data (Kruize et al., 2016; O'Grady & O'Hare, 2017).

Rules and Conditions: Data management changes according to each sector characteristics and background; thus, the application of data sharing and control practices should be altered and evaluated in contextual environments based on individual case specifics. The agricultural managers and policymakers should identify the right collaborative relationships through the proposed framework among the different stakeholders to enable the adoption of smart farming practices even at the farmers' point. The farmers should also be aware of the different role-based access control policies and how they may impact their collaborative relationships with other supply chain actors. The policies will help them understand how their data is used across the supply chain and eliminate data-sharing concerns. The scenario of the smart farm presented the way the framework can be applied in order to inform the AI- enforced rules and conditions (through argumentation reasoning) to be set in data sharing platforms.

There are several opportunities and challenges manifested through the Agriculture 4.0 paradigm. Our study presented an example case to show how one of the multiple challenges (data sharing among Agricultural platforms through agricultural activities) could be addressed through AI approaches. The next subsestions will explain the potential contributions to theory, policy, and practice presented through this study.

5.1 Theoretical implications

In the smart farm scenario, we illustrate the applicability of the DSA Framework for AI-enforced role-based access control for agricultural platforms and we contribute further in the literature of data management (Hazen et al., 2014; Karafili et al., 2018b) and specifically the relevant AI applications for decision making (Duan et al., 2019). We argue that agricultural stakeholders (and other stakeholders depending on the application sector) can use this framework as a template for AI commands and logical decisions in terms of how the data will be handled by the variety of actors involved in the food systems and have access to farming platforms for various reasons (Spanaki, Karafili, et al., 2021; Spanaki, Sivarajah, et al., 2021). The application of AI role-based access control rules and conditions also expands the background of the agricultural supply chains and the sector as a whole, as there is a requirement for contextual information to define the proposed DSA design. From an ecosystems' perspective we contribute also to the academic discussions about data-driven innovation (Shahriar Akter et al., 2019; Shahriar Akter, Michael, Uddin, McCarthy, & Rahman, 2020; Pappas et al., 2018), but also data governance which is discussed as a major challenge of data management (Mikalef, Boura, et al., 2020; Paul P. Tallon, Ramirez, & Short, 2013).

The study contributes to the contextual and theoretical background of data management through the presentation of a framework of AI techniques as a solution to data sharing problems. The role-based access control framework can be used as a template for contextual applications of AI-driven data sharing decisions in various sectors (e.g., retail, healthcare, aerospace, manufacturing etc.). The design science approach followed in the study is putting into force the background of the agricultural sector to present contextual information and to define the role-based access control decisions in the case of smart farms from a computational perspective. In Agriculture 4.0, data sharing control presents the urgency for data governance and control across the different agricultural stakeholders (Janssen, Brous, Estevez, Barbosa, & Janowski, 2020), but that is also a general requirement for Industry 4.0 paradigm. The scope is formed around the data exchange in the collaborative relationships (through the Agricultural digital platforms) among different stakeholders. Besides, the context of information sharing is extended with the collaboration aspect in the agricultural context (Despoudi et al. 2018; Matopoulos et al. 2007; Daugherty 201; Papetti et al. 2012; Yan et al. 2016), where the challenge of data sharing and access control decisions across are examined. Therefore, the proposed framework draws on the literature streams of the agricultural sector and data management, where the various aspects of the setting (actors-relationships) and data quality attributes (types of data) assist in a combination to define and design the proposed solution (conditions informing the AI technique).

5.2 Implications for policy and practice

The proposed design offers then, by applying the DSA aspects and exploring them through the framework of role-based data access control, lessons and/or guidelines per each of these aspects to agricultural stakeholders (or any stakeholders depending on the scenario) who would like to adopt and use various platforms and AI applications in the farming practices. In terms of practical contributions, the framework develops usable considerations and recommendations for the pre-implementation phase of digital platforms (in agricultural context or in any other context) and implementation guidelines that enable potential users (in this case farmers and farming stakeholders) to leverage the value of data and information and develop a precise and tailored experience in the associated practices (farming practices at this instance). The framework identifies the actors, relationships and the conditions that could be in place as a checklist of important aspects to consider for digital transformation in a specific sector but also the individual firm (i.e., farm). Identifying the guidelines before and post implementation, can assist in greater impact of digital technologies within specific sector and context, while understanding the requirements of the field, but also the data sharing policies, power and control relationships around that context. Below the implications in terms of the platforms, the stakeholders and the sector are described briefly, to provide pre-implementation considerations when designing and acquiring the platforms.

Platform-specific considerations

- *Platform requirements*. For role-based access control, the initial step should be to understand and define the associated requirements to be defined for the proposed DSA, provides a frame to define the relevant ecosystem of actors, relationships but also the types of data used, collected, and entered in the systems, and therefore a frame to define the relevant practices but also policies for the specific setting (i.e., agriculture) that can be applied.
- *Platform governance.* Acquiring knowledge of who has roles in the systems and how the systems are monitored and governed, as well as the regulatory and policy requirements. The proposed AI approach highlights the need to design and implement context-specific data sharing control policies to define the relationships among the agricultural stakeholders.

- *Data governance policies.* Application of data governance policies in various sectors will eliminate the data-sharing concerns arising through multiple digital platforms and reform the stakeholders' relationships across the SC (Giannakis, Spanaki, & Dubey, 2019). For the Agricultural sector, relevant agricultural policies should be designed to set the boundaries regarding data sharing control points in the agricultural platforms; this could be in sector specific DSAs and a broader context, general DSAs. The DSAs and policies should also include role-based access control for each of the different agricultural stakeholders using multiple digital platforms (Karafili et al., 2018b). All the above will enable and accelerate the adoption of smart farming practices, primarily at the farmers' point and for all the stakeholders involved in the supply chain.

Stakeholder-specific considerations

- *Knowledge and skills.* Many individual farms have started already applying AI solutions and various farming platforms, however there is still lack of knowledge and skills in regard to how rapidly the systems change in the AgriTech field and how efficient could be this change, how the actors could cooperate in a smoother and timely manner to minimise risk and endeavour the benefits. The users of the systems should receive initial training and understanding of the systems and also follow the updates of newer versions, in order to endeavour the full potential of such technology.
- *Impact to the customer.* How the use of such technologies could impact the end product-service of the farm and the experience of the customer, in terms of product quality, traceability, sustainability of the process. The end results to the customer end should also be monitored and feed the digital platforms with usable feedback, so as the various practices are enhanced and tailored to provide value also for the customer.

Sector-specific considerations

- *Central governance and understanding of the sector.* Governmental parties and stakeholders in the farming sector, could better understand the field and the requirements, while they can apply specific policies for farms but also the farmers, based on real-time context-specific data and insight.
- *Sustainability and resilience.* Through real-time information and data, the sector could benefit from precise predictions and advice, so as in cases of humanitarian crises there will be a proactive response and not reactive measurements that could cost big losses in terms of resilience but also the sustainability of the farming production and the maintenance of the farming fields.

From a practical perspective, as many individual farms have started already applying AI solutions and various farming platforms, there is still lack of knowledge and skills in regard to how rapidly the systems change in the AgriTech field and how efficient could be this change, how the actors could cooperate in a smoother and timely manner to minimise risk and endeavour the benefits. Other questions that could be raised about the use of AI applications in agricultural sector could vary in terms of the impact to customer, the way the systems are monitored and governed, as well as the regulatory and policy requirements (Dwivedi et al., 2021; Kamble, Gunasekaran, Parekh, & Joshi, 2019; Sharif & Irani, 2016).

5.3 Limitations and future research directions

Although Agriculture 4.0 has several advantages, it comes with sector-specific and technological challenges. The potential of Agriculture 4.0 smart farming models for farmers is high, but there are concerns about the focus of future research. From the farmers perspective, there has been resistance and challenges in smart farming implementation, with the main inhibitors being the availability and use of new technology and the data-sharing concerns. In our study, we proposed a new approach for the latter, the data sharing between farms. We argued that data can be processed and can create value through tailoring techniques across the immediate boundaries of each farm with well-defined DSAs, role-based access control and usage control policies. The major limitation of this study is the fact it it context specific, and could be studied from various approaches for the individual smart farm, but also a wider farming context (depends on the location, country, culture of the area/region, size of the farm etc). Futher research towards this direction could explore more case scenarios to address further these context specifics. Another limitation draws on the fact that the data sharing could be applied and compared within other contexts different from the agricultural sector, to highlight the sector-related challenges, but also the various other aspects of the DSAs. Longitudinal and qualitative studies on the field (interviews or surveys with stakeholders etc) exploring the behaviours of the actors and their decisions would enhance the field with context-rich information and assist in defining precise DSAs while informing the AI-enabled techniques in place.

Future research in this field should focus on exploring sustainability and the ethical and practical concerns of Agriculture 4.0. The data sharing context for heterogeneous data, the path to better data quality, and frameworks that describe and track data processing in other sectors should also be further researched. The current presented framework can be easily applied using the sticky policy paradigm, and the DSAs enforced when a cloud environment is used. Further studies should be continued to be made on ensuring the security properties of the data. In particular, the data privacy aspect should be considered in future research as it poses severe threats in data sharing among third parties. The organisational aspects and the capabilities and skills needed to build innovation in data-intensive contexts should be examined as part of the data generation and exploitation strategies.

6 Conclusion

In light of the fourth industrial revolution (Industry 4.0), the view of the' smart farms' provides a new approach to traditional farming as a matter of urgency for the sustainability of the existing food systems and agricultural supply chains. Agriculture 4.0, or else called the smart farming paradigm, is seen as a logical development of previous food production systems. The challenge of feeding the world's population ecologically and sustainably requires viable solutions to increase food production and environmental efficiency. Both the radical changes implied by Agriculture 4.0, Industry 4.0 and the technological infrastructure could provide a ground for the agricultural sector to have the most significant disruption and significant potential for innovation over the future years.

The context of Agriculture 4.0 emphasises on the use of data and technology in the cyber-physical farm management cycle, with a strong focus on data-intensive, informed decisions for for the farming sector (Kaloxylos et al., 2012; Nukala et al., 2016; Spanaki, Karafili, et al., 2021; Spanaki, Sivarajah, et al., 2021; Wolfert et al., 2017). As described by Wolfert et al. (2017) the use of smart farming in agricultural sector data may unravel in a continuum of three directions:

1. Farmers and other stakeholders of the agricultural sector as participants in closed, proprietary systems of a highly integrated Agri-Food supply chain.
2. Farmers and other stakeholders as parts of a collaborative supply chain network, sharing data, information and experience with their peers via online platforms.
3. Farmers and other stakeholders as knowledge/information sharing and decision-making entities of a supply chain network of open, collaborative systems flexible in choosing business partners as well for the technology as for the food production side.

In all three directions, the development of data platforms and infrastructures as well as the regulatory and legal frameworks around the use of data are essential aspects for the individual farmers and the farming sector as a whole. Our study focuses on the challenge of data sharing and control, which can also base sustainable operating models for smart farming and, overall, the agricultural sector, especially for small and medium farms.

References

Akter, S, Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? International Journal of Production Economics, 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Akter, Shahriar, Bandara, R., Hani, U., Fosso Wamba, S., Foropon, C., & Papadopoulos, T. (2019). Analytics-based decision-making for service systems: A qualitative study and agenda for future research. International Journal of Information Management. https://doi.org/10.1016/j.ijinfomgt.2019.01.020

Akter, Shahriar, Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2020). Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics. Annals of Operations Research. https://doi.org/10.1007/s10479-020-03620-w

Angelopoulos, S., Brown, M., McAuley, D., Merali, Y., Mortier, R., & Price, D. (2021). Stewardship of Personal Data on Social Networking Sites. *International Journal of Information Management*, *56*, 102208, 11. https://doi.org/10.1016/j.ijinfomgt.2020.102208

Angelopoulos, S., McAuley, D., Merali, Y., Mortier, R., & Price, D. (2016). Small Fish in a Big Pond: An Architectural Approach to Users Privacy, Rights and Security in the Age of Big Data. *ICIS 2016 Proceedings*, 1–18. Retrieved from http://aisel.aisnet.org/icis2016/ISDesign/Presentations/8

Barmpounakis, S., Kaloxylos, A., Groumas, A., Katsikas, L., Sarris, V., Dimtsa, K., … Wolfert, S. (2015). Management and control applications in Agriculture domain via a Future Internet Business-to-Business platform. Information Processing in Agriculture, 2(1), 51-63. https://doi.org/10.1016/j.inpa.2015.04.002

Bondarenko, A., Dung, P. M., Kowalski, R. A., & Toni, F. (1997). An abstract, argumentation-theoretic approach to default reasoning. Artificial Intelligence, 93(1–2), 63–101. https://doi.org/10.1016/S0004-3702(97)00015-5

Cao, M., Vonderembse, M. A., Zhang, Q., & Ragu-Nathan, T. S. (2010). Supply chain collaboration: conceptualisation and instrument development. International Journal of Production Research, 48(22), 6613–6635. https://doi.org/10.1080/00207540903349039

CEMA - European Agricultural Machinery. (2017a). Digital Farming: what does it really mean? Retrieved from http://www.cema-agri.org/page/digital-farming-what-does-it-really-mean

CEMA - European Agricultural Machinery. (2017b). FARMING 4.0: THE FUTURE OF AGRICULTURE? Retrieved from http://www.cema-agri.org/page/farming-40-future-agriculture

Daugherty, P. J. (2011). Review of logistics and supply chain relationship literature and suggested research agenda. International Journal of Physical Distribution and Logistics Management, 41(1), 16-31. https://doi.org/10.1108/09600031111101402

Christiaanse, E., Diepen, T. Van, & Damsgaard, J. (2004). Proprietary versus internet technologies and the adoption and impact of electronic marketplaces. *Journal of Strategic Information Systems*, *13*(2), 151–165. https://doi.org/10.1016/j.jsis.2004.02.004

Despoudi, S., Papaioannou, G., Saridakis, G., & Dani, S. (2018). Does collaboration pay in agricultural supply chain? An empirical approach. International Journal of Production Research, 56(13), 4396-4417. https://doi.org/10.1080/00207543.2018.1440654

Driscoll, M. (2012). How can we build a sustainable farming system for all? The Guardian Sustainable Business. Retrieved from http://www.theguardian.com/sustainable-business/blog/farming-system-principles-based-sustainable

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. International Journal of Information Management, 48, 63-71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dung, P. M. (1995). On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. Artificial Intelligence, 77(2), 321–357. https://doi.org/10.1016/0004-3702(94)00041-X

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994 . https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Feki, M., Boughzala, I., & Wamba, S. F. (2016). Big Data Analytics-Enabled Supply Chain Transformation: A Literature Review. Proceedings of the 2016 49th Hawaii International Conference on System Sciences (HICSS), 1123–1132. IEEE Computer Society.

Fiala, P. (2005). Information sharing in supply chains. Omega, 33(5), 419–423. https://doi.org/10.1016/j.omega.2004.07.006

Giannakis, M., Spanaki, K., & Dubey, R. (2019). A cloud-based supply chain management system: effects on supply chain responsiveness. Journal of Enterprise Information Management, 32(4). https://doi.org/10.1108/JEIM-05-2018-0106

Gregor, S., & Hevner, A. R. (2011). Introduction to the special issue on design science. Information Systems and E-Business Management, 9(1), 1–9. https://doi.org/10.1007/s10257-010-0159-8

Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. International Journal of Production Economics, 154, 72–80. https://doi.org/10.1016/j.ijpe.2014.04.018

Hevner A., Chatterjee S. (2010) Design Science Research in Information Systems. In: Design Research in Information Systems. Integrated Series in Information Systems, vol 22. Springer, Boston, MA. https://doi.org/10.1007/978-1-4419-5653-8_2

Hevner, A., March, S., Park, J., & Ram, S. (2004). Design science in information systems research. MIS Quarterly: Management Information Systems, 28(1), 75–105. https://doi.org/10.2307/25148625

Holmström, J., Ketokivi, M., & Hameri, A. P. (2009). Bridging practice and theory: A design science approach. Decision Sciences, 41(4), 1001. https://doi.org/10.1111/j.1540-5915.2008.00221.x

Hughes, L., Dwivedi, Y. K., Rana, N. P., Williams, M. D., & Raghavan, V. (2020). Perspectives on the future of manufacturing within the Industry 4.0 era. Production Planning & Control, 1-21. https://doi.org/10.1080/09537287.2020.1810762

Iakovou, E., Vlachos, D., Achillas, C., & Anastasiadis, F. (2014). Design of sustainable supply chains for the agrifood sector: A holistic research framework. Agricultural Engineering International: CIGR Journal, 16, 1-10.

Ioannou, A., Tussyadiah, I., & Lu, Y. (2020). Privacy concerns and disclosure of biometric and behavioral data for travel. *International Journal of Information Management, 54,* 102122. https://doi.org/10.1016/j.ijinfomgt.2020.102122

Irani, Z., Sharif, A. M., Lee, H., Aktas, E., Topaloğlu, Z., van't Wout, T., & Huda, S. (2018). Managing food security through food waste and loss: Small data to big data. Computers and Operations Research, 98, 367-383. https://doi.org/10.1016/j.cor.2017.10.007

Jaffee, S., Siegel, P., & Andrews, C. (2010). Rapid agricultural supply chain risk assessment: A conceptual framework. Agriculture and rural development discussion paper, 47(1), 1-64. Retrieved from https://www.marketlinks.org/sites/default/files/media/file/2020-10/Test.pdf

Ji, C., Jia, F., & Xu, X. (2018). Agricultural co-operative sustainability: Evidence from four Chinese pig production co-operatives. Journal of Cleaner Production, 197 (Part 1), 1095-1107. https://doi.org/10.1016/j.jclepro.2018.06.279

Jones-Farmer, L., Ezell, J. D., & Hazen, B. T. (2014). Applying Control Chart Methods to Enhance Data Quality. Technometrics, 56(1), 29–41. https://doi.org/10.1080/00401706.2013.804437

Kakas, A., Kowalski, R., & Toni, F. (1992). Abductive logic programming. Journal of Logic and Computation, 2(6), 719–770. https://doi.org/10.1093/logcom/2.6.719

Kakas, A., Van Nuffelen, B., & Denecker, M. (2001). A-system: Problem solving through abduction. IJCAI International Joint Conference on Artificial Intelligence. https://doi.org/10.1007/3-540-45402-0_29

Kaloxylos, A., Eigenmann, R., Teye, F., Politopoulou, Z., Wolfert, S., Shrank, C., … Kormentzas, G. (2012). Farm management systems and the Future Internet era. Computers and Electronics in Agriculture, 89, 130-144. https://doi.org/10.1016/j.compag.2012.09.002

Kamble, S. S., Gunasekaran, A., Parekh, H., & Joshi, S. (2019). Modeling the internet of things adoption barriers in food retail supply chains. Journal of Retailing and Consumer Services, 48, 154-168 . https://doi.org/10.1016/j.jretconser.2019.02.020

Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture, 143, 23-37. https://doi.org/10.1016/j.compag.2017.09.037

Karafili, E., & Lupu, E. C. (2017). Enabling Data Sharing in Contextual Environments. Proceedings of the 22nd ACM on Symposium on Access Control Models and Technologies - SACMAT '17 Abstracts, 231–238. https://doi.org/10.1145/3078861.3078876

Karafili, E., Spanaki, K., & Lupu, E. C. (2018a). Access control and quality attributes of open data: Applications and techniques. Lecture Notes in Business Information Processing, 339, 603-614. https://doi.org/10.1007/978-3-030-04849-5_52

Karafili, E., Spanaki, K., & Lupu, E. C. (2018b). An argumentation reasoning approach for data processing. Computers in Industry, 94, 52-61. https://doi.org/10.1016/j.compind.2017.09.002

Kowalski, R. (2011). Computational logic and human thinking: How to be artificialy intelligent. In Computational Logic and Human Thinking: How to be Artificialy Intelligent. https://doi.org/10.1017/CBO9780511984747

Kruize, J. W., Wolfert, J., Scholten, H., Verdouw, C. N., Kassahun, A., & Beulens, A. J. M. (2016). A reference architecture for Farm Software Ecosystems. Computers and Electronics in Agriculture 125, 12-28. https://doi.org/10.1016/j.compag.2016.04.011

Kumar, R., Singh, R. K., & Dwivedi, Y. K. (2020). Application of industry 4.0 technologies in SMEs for ethical and sustainable operations: Analysis of challenges. Journal of cleaner production, 275, 124063.

Lamborelle, A. (2016). Farming 4.0: The future of agriculture? EURACTIV.com Retrieved from https://www.euractiv.com/section/agriculture-food/infographic/farming-4-0-the-future-of-agriculture/

Manzini, R., & Accorsi, R. (2013). The new conceptual framework for food supply chain assessment. Journal of Food Engineering, 115(2), 251-263 . https://doi.org/10.1016/j.jfoodeng.2012.10.026

Matopoulos, A., Vlachopoulou, M., Manthou, V., & Manos, B. (2007). A conceptual framework for supply chain collaboration: Empirical evidence from the agri-food industry. Supply Chain Management: An International Journal, 12(3), 177-186. https://doi.org/10.1108/13598540710742491

Matteucci, I., Petrocchi, M., & Sbodio, M. L. (2010). CNL4DSA: A controlled natural language for data sharing agreements. Proceedings of the ACM Symposium on Applied Computing. https://doi.org/10.1145/1774088.1774218

Mena, C., Adenso-Diaz, B., & Yurt, O. (2011). The causes of food waste in the supplier-retailer interface: Evidences from the UK and Spain. Resources, Conservation and Recycling, 55(6), 648-658,. https://doi.org/10.1016/j.resconrec.2010.09.006

Meola, A. (2016). Why IoT, Big Data & Smart Farming is the Future of Agriculture - Business Insider Deutschland. Report of Food and Agriculture Organization of the United Nations. Retrieved from http://www.fao.org/e-agriculture/news/why-iot-big-data-smart-farming-are-future-agriculture

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. British Journal of Management, *30*(2), 272-298. https://doi.org/10.1111/1467-8551.12343

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2020). The role of information governance in big data analytics driven innovation. Information and Management, *57*(7), 103361. https://doi.org/10.1016/j.im.2020.103361

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information and Management, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Mikalef, P., Pappas, I. O., Krogstie, J., & Pavlou, P. A. (2020). Big data and business analytics: A research agenda for realizing business value. Information and Management, 57(1), 103237. https://doi.org/10.1016/j.im.2019.103237

Nukala, R., Panduru, K., Shields, A., Riordan, D., Doody, P., & Walsh, J. (2016). Internet of Things: A review from "Farm to Fork." In *2016 27th Irish Signals and Systems Conference (ISSC)* (pp. 1-6). IEEE. https://doi.org/10.1109/ISSC.2016.7528456

O'Grady, M. J., & O'Hare, G. M. P. (2017). Modelling the smart farm. Information Processing in Agriculture, 4(3), 179-187. https://doi.org/10.1016/j.inpa.2017.05.001

O'Keefe, R. (2014). Design Science, the design of systems and Operational Research: Back to the future. Journal of the Operational Research Society, 65(5), 673-684. https://doi.org/10.1057/jors.2012.175

Otjacques, B., Hitzelberger, P., & Feltz, F. (2007). Interoperability of E-government information systems: Issues of identification and data sharing. *Journal of Management Information Systems*, *23*(4). https://doi.org/10.2753/MIS0742-1222230403

Papaioannou, G., Mohammed, A. M., Despoudi, S., Saridakis, G., & Papadopoulos, T. (2020). The role of adverse economic environment and human capital on collaboration within agri-food supply chains. *International Journal of Information Management 52,* 102077. https://doi.org/10.1016/j.ijinfomgt.2020.102077

Papadopoulos, T., Singh, S. P., Spanaki, K., Gunasekaran, A., & Dubey, R. (2021). Towards the next generation of manufacturing: implications of big data and digitalization in the context of industry 4.0. Production Planning and Control. https://doi.org/10.1080/09537287.2020.1810767

Pappas, I. O., Mikalef, P., Giannakos, M. N., Krogstie, J., & Lekakos, G. (2018). Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. Information Systems and E-Business Management, 16, 479–491. https://doi.org/10.1007/s10257-018-0377-z

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2008). A Design Science Research Methodology for Information Systems Research. Journal of Management Information Systems, 24(3), 45–77. https://doi.org/10.2753/mis0742-1222240302

Pham, X., & Stack, M. (2018). How data analytics is transforming agriculture. Business Horizons, 61(1), 125-133 . https://doi.org/10.1016/j.bushor.2017.09.011

Pomerol, J. C. (1997). Artificial intelligence and human decision making. European Journal of Operational Research, *99*(1), 3-25. https://doi.org/10.1016/S0377-2217(96)00378-5

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2014). How information-sharing values influence the use of information systems: An investigation in the business intelligence systems context. *Journal of Strategic Information Systems*, *23*(4), 270–283. https://doi.org/10.1016/j.jsis.2014.08.003

Prahinski, C., & Benton, W. C. (2004). Supplier evaluations: Communication strategies to improve supplier performance. Journal of Operations Management, 22(1), 39–62. https://doi.org/10.1016/j.jom.2003.12.005

Pretty, J. (2008). Agricultural sustainability: Concepts, principles and evidence. Philosophical Transactions of the Royal Society B: Biological Sciences, *363*(1491), 447-465. https://doi.org/10.1098/rstb.2007.2163

Shareef, M. A., Kumar, V., Dwivedi, Y. K., Kumar, U., Akram, M. S., & Raman, R. (2021). A new health care system enabled by machine intelligence: Elderly people's trust or losing self control. Technological Forecasting and Social Change, 162, 120334.

Sharif, A. M., & Irani, Z. (2016). People, process and policy perspectives on food security: An exploration using systems archetypes. Transforming Government: People, Process and Policy, 10 (3), 359-367. https://doi.org/10.1108/TG-01-2016-0008

Sheu, C., Yen, H. J. R., & Chae, B. (2006). Determinants of supplier-retailer collaboration: evidence from an international study. International Journal of Operations & Production Management, 26(1), 24–49. https://doi.org/10.1108/01443570610637003

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. Journal of Business Research, 70, 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001

Soosay, C. A., Hyland, P. W., & Ferrer, M. (2008). Supply chain collaboration: Capabilities for continuous innovation. Supply Chain Management, 13(2), 160-169. https://doi.org/10.1108/13598540810860994

Spanaki, K., Gürgüç, Z., Adams, R., & Mulligan, C. (2018). Data supply chain (DSC): research synthesis and future directions. International Journal of Production Research, 56(13), 4447-4466. https://doi.org/10.1080/00207543.2017.1399222

Spanaki, K., Karafili, E., Sivarajah, U., Despoudi, S., & Irani, Z. (2021). Artificial intelligence and food security: swarm intelligence of AgriTech drones for smart AgriFood operations. Production Planning and Control. https://doi.org/10.1080/09537287.2021.1882688

Spanaki, K., Sivarajah, U., Fakhimi, M., Despoudi, S., & Irani, Z. (2021). Disruptive technologies in agricultural operations: a systematic review of AI-driven AgriTech research. Annals of Operations Research. https://doi.org/10.1007/s10479-020-03922-z

Spanoudakis, N. I., Constantinou, E., Koumi, A., & Kakas, A. C. (2017). Modeling data access legislation with Gorgias. In *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems* (pp. 317-327). Springer, Cham. https://doi.org/10.1007/978-3-319-60045-1_34

Spanoudakis, N. I., Kakas, A. C., & Moraitis, P. (2017). Conflicts resolution with the SoDA methodology. In *International Workshop on Conflict Resolution in Decision Making* (pp. 82-99). Springer, Cham. https://doi.org/10.1007/978-3-319-57285-7_6

Swarup, V., Seligman, L., & Rosenthal, A. (2006). Specifying data sharing agreements. Proceedings - Seventh IEEE International Workshop on Policies for Distributed Systems and Networks, Policy 2006, 2006, 157–160. https://doi.org/10.1109/POLICY.2006.34

Tallon, Paul P. (2013). Corporate governance of big data: Perspectives on value, risk, and cost. *Computer*, *46*(6), 32-38. https://doi.org/10.1109/MC.2013.155

Tallon, Paul P., Ramirez, R. V., & Short, J. E. (2013). The information artifact in IT governance: Toward a theory of information governance. Journal of Management Information Systems, 30(3), 141–177. https://doi.org/10.2753/MIS0742-1222300306

Tsolakis, N. K., Keramydas, C. A., Toka, A. K., Aidonis, D. A., & Iakovou, E. T. (2014). Agrifood supply chain management: A comprehensive hierarchical decision-making framework and a critical taxonomy. Biosystems Engineering, *120*, 47-64. https://doi.org/10.1016/j.biosystemseng.2013.10.014

UN Food and Agriculture Organization. (2011). Global Food Losses and Waste. Report of Food and Agriculture Organization of the United Nations. Retrieved from http://www.fao.org/fileadmin/user_upload/ags/publications/GFL_web.pdf

UN Food and Agriculture Organization. (2017). The state of food and agriculture. Report of Food and Agriculture Organization of the United Nations. Retrieved from http://uni-sz.bg/truni11/wp-content/uploads/biblioteka/file/TUNI10042440(1).pdf

UNCTAD. (2016). Agricultural commodity value chains: The effects of market concentration on farmers and producing countries – the case of cocoa. United Nations Conference on Trade and Development. https://doi.org/10.1080/1356346032000138096

van Aken, J. (2005). Management research as a design science: Articulating the research products of mode 2 knowledge production in management. British Journal of Management, *16*(1), 19-36. https://doi.org/10.1111/j.1467-8551.2005.00437.x

van Aken, J., Chandrasekaran, A., & Halman, J. (2016). Conducting and publishing design science research: Inaugural essay of the design science department of the Journal of Operations Management. Journal of Operations Management, *47*, 1-8. https://doi.org/10.1016/j.jom.2016.06.004

Wamba, S. F., Akter, S., Coltman, T., & Ngai, E. W. T. (2015). Guest editorial: Information technology-enabled supply chain management. Production Planning and Control, 26(12), 933–944. https://doi.org/10.1080/09537287.2014.1002025

Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014

Weltzien, C. (2016). Digital agriculture - or why agriculture 4.0 still offers only modest returns. Landtechnik, *71*(2), 66-68.. https://doi.org/10.15150/lt.2015.3123

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big Data in Smart Farming – A review. Agricultural Systems, *153*, 69-80. https://doi.org/10.1016/j.agsy.2017.01.023

Yahya, N. (2018). Agricultural 4.0: Its implementation toward future sustainability. In Green Energy and Technology, 125-145.. https://doi.org/10.1007/978-981-10-7578-0_5

Yeganeh, N. K., Sadiq, S., & Sharaf, M. A. (2014). A framework for data quality aware query systems. Information Systems, 46, 24–44. https://doi.org/http://dx.doi.org/10.1016/j.is.2014.05.005

Zissis, D., Aktas, E., & Bourlakis, M. (2017). A New Process Model for Urban Transport of Food in the UK. Transportation Research Procedia, *22*, 588-597. https://doi.org/10.1016/j.trpro.2017.03.048