Socio-Technical Challenges Impacting Data Quality in Agriculture: An Integrated Review

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***Abstract* - The agricultural sector is becoming more digitalised, where data is crucial for decision-making to improve food security and sustainability. Thus, making successful decisions dependent on high data quality (DQ). However, the quality of agricultural data (agri-data) faces numerous challenges that stem from the complex interaction between social and technical approaches. This study presents an integrated socio-technical view of challenges affecting the quality of agri-data. We identified the following social challenges: (1) digital and data literacy limitations; (2) trust and data sharing, (3) knowledge and cultural resistance, (4) organisational challenges; and technical challenges: (5) systems interoperability and integration, (6) infrastructure and scalability, (7) temporal and spatial data validation complexity, (8) data heterogeneity and standardisation, (9) data sovereignty. The findings reveal that socio-technical challenges are interconnected. In order to create effective solutions, it is required to address DQ of agri-data through a holistic view that considers people, organisational and technical aspects equally, with regard to their data collection, validation, sharing and use. This integrated perspective offers valuable insights for researchers, policymakers and technology providers working to enhance the DQ and trustworthiness of data ecosystems in agriculture.**

Keywords—Agricultural Data, Data Quality, Smart Farming, IoT, Socio-Technical, Challenges

I. INTRODUCTION

The agricultural sector is currently going through a significant transformation, with farming practices becoming more data-driven [5, 38]. This transformation is motivated by the introduction of modern agricultural management, such as precision agriculture and smart farming technologies [31, 49, 62]. Precision agriculture is described as an approach that deploys technology and techniques to measure in-field variability precisely, to enhance the efficiency of agricultural production [21, 49]. For instance, using GPS-guided tractors with variable rate technology, farmers can exactly apply fertilisers only to the area needed, hence avoiding crops and surrounding areas from overapplication [62]. Whereas smart farming goes beyond precision agriculture. It is an advancement that focuses on using both information and communication technology to get notifications and insights [21, 49]. For example, a field has sensors that automatically detect when crops need irrigation and turn on sprinklers, while sending alerts to the farmer's phone about the weather changes and pest threats. These modern agricultural management practices have brought opportunities for farmers to optimise their resources, enhancing quality, production and sustainability [50]. Thereby, data collection, integration, validation and sharing of diverse agri-data became the centre of this transformation [11, 49].

However, the promising benefits of data-driven agriculture rely on the high quality of agri-data [11, 14, 45]. Reference [6] points out that in 2016, poor DQ caused a loss of 3.1 trillion dollars to the United States. Poor DQ refers to inaccurate, incomplete, inconsistent, irrelevant or outdated data, making it unreliable for decision-making purposes [44]. It occurs when data contains errors, duplicates, missing values or fails to meet the standards and requirements necessary for its intended use [49]. When analysing the negative economic impacts of poor DQ in agriculture, the consequences go beyond monetary losses [14, 44], as sustainability and food security pose a significant concern for human health and environmental repercussions [29]. As a result, DQ shifts from a "nice to have" scenario to a "necessity" in agriculture. Nevertheless, achieving DQ is still challenging [6, 11, 15]. In line with that, [15] emphasises that DQ challenges comprise one or multiple factors. Whereas [1] points out that challenges related to people and organisational (i.e., socio), and technology (technical) must be considered to enable an in-depth understanding of the factors impacting DQ. Despite growing recognition of social and technical approaches in smart farming [26, 33, 54], DQ remains limited with many challenges towards an integrated perspective. Most studies focus on technical aspects of agri-data management [2, 3, 8, 11, 21, 28, 31, 36, 52], on social aspects of technology adoption [14, 29], or socio-technical aspects without examining their interactions in the context of DQ [5, 19, 26, 33, 50]. Therefore, an integrated perspective on the socio-technical challenges associated with agricultural DQ has not been explored in existing research yet. Aiming at filling this research gap, this study focuses on answering the following research question: "What are the socio-technical challenges impacting the quality of agri-data?" This question is addressed through a literature review. By adopting the socio-technical systems theory [23], a more comprehensive understanding of the barriers to agricultural DQ is identified toward more effective data management practices.

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II. Background

The key concepts of this study are described in four sub-sections as follows: a) Agricultural Sector, b) Agri-Data, c) Data Quality and d) Theoretical Foundation.

A) Agricultural Sector

Agriculture is considered one of the oldest activities in history [58]. Its name derives from the Latin words "ager" (field) and "colo" (cultivate), which refers to a field being cultivated [42]. Despite the meaning being more restrictive to crop cultivation, the term agriculture broadly encompasses several ways in which crops, plants and domestic animals support the worldwide human population by supplying food and other essential products [2, 42].

Despite playing an important role in the gross domestic product (GDP) of countries, the agricultural sector still faces myriad issues, such as sustainability, climate change, animal welfare, impact on wildlife and landscape [40, 50]. Those issues have an immense impact on farmers' businesses and could even potentially lead to a cessation of operations. For instance, approximately 1,400 Irish farmers have ceased their operations every year, with a total of 8,773 farmers having left farming since 2016 [4]. In order to support farmers in handling some of these issues, the use of technology and data became a key pillar. For instance, farmers use new machinery and IoT devices that can track their activities by collecting agri-data to help them optimise their operations, hence contributing to solving some of the aforementioned issues [50].

B) Agri-Data

Despite data being intangible, they are real-world objects [41]. Through technological advancements in the agricultural sector, new machinery and IoT devices enable farmers to produce and share data [31, 38]. Data is composed of isolated facts and observations, which are registered in a database, processed and communicated across a network [15, 55]. Data is highly contextual [41]; therefore, agri-data is associated with the agricultural operations [17]. For instance, agri-data is composed of information on livestock and fish, agronomic and land, machinery, climate, financial and compliance data [17]. Reference [2] specifies that agri-data has multiple and specific attributes necessary for farmers to conduct their business activities, such as soil characteristics, crop performance and market trends. Considering the existence of sub-areas of agriculture, ranging from crops, livestock and fisheries [42], the variety of devices and methods to collect data according to farmers' needs and tasks results in diverse agri-data formats and contents with different volumes [21]. Nevertheless, agri-data is beneficial only if it is of high quality and reliable for decision-making [45, 52].

C) Data Quality

Achieving DQ represents a complex concept that has been desired in all domains [6, 44, 45, 51]. Since the agricultural sector is becoming data-driven for making decisions [35], DQ is fundamental for making this asset valuable [15].

Although research on DQ produces valuable insights, it is dependent on the use case and domain [27]. Thus, several definitions in different fields have emerged [6, 51]. Thereby, investigating and designing for better quality interventions requires first understanding what quality means and how it is measured [53]. According to the International Organisation for Standardisation (ISO), DQ refers to a degree wherein a set of inherent characteristics of data fulfils requirements [22]. Whereas the experts [44] describe DQ as the data that is fit for use by data consumers, more specifically, by those who use data. This perspective has a similar concept to the ISO, since users are the ones who can judge whether the data meets their needs or not [25]. In contrast, the study [45] emphasises DQ to be an outcome of a combination of practices to provide more reliable information to its users.

Besides being a multi-dimensional concept on qualitative and quantitative attributes (also known as dimensions) [30], DQ is also referred to as a multi-disciplinary problem [15, 24, 53]. According to reference [6], the lack of standardisation and methodological rigour to establish and interpret DQ, has led to more than 300 DQ dimensions. These dimensions are often used to measure the quality of the data in terms of accuracy, completeness, consistency, relevance, timeliness, trustworthiness of the data, among many others [16, 27, 30, 53], hence making it harder to select which dimension is most suitable [6]. Therefore, the study [16] points out that to properly address data quality or its specific dimension, it is important to consider the factors that influence it.

D) Theoretical Foundation

The Socio-Technical Systems (STS) theory offers a valuable lens for understanding the complexity and challenges around DQ in agriculture. It was established by the Tavistock Institute in 1950 to emphasise the reciprocal interrelationship between machines and people, as their efficiency is no longer contradictory, but rather a joint and optimised performance for better results [23, 34]. Thus, the STS theory is the most suitable theory to guide this study.

In the information systems (IS) field, scholars have applied socio-technical approaches to understand implementation challenges and user adoption [10, 37]. Within the agricultural sector, reference [26] supports socio-technical design for developing a livestock management system. They argue that those socio-technical approaches became crucial for systems implementations, especially for small and medium-scale farmers. Thus, solutions must accommodate limited resources, infrastructure constraints, and diverse user capabilities [26]. Therefore, technical solutions alone are insufficient when not aligned with the social contexts and user needs [10]. In line with the STS theory [23], challenges regarding DQ in agriculture should be investigated as a whole rather than on isolated technical or social approaches.

III. Research Approach

This study follows a Design Science Research Methodology (DSRM) proposed by [7]. In order to start the first phase of the DSRM, to define the problem and motivation of a study [32], we followed a scoping review approach by [60] to explore existing literature. Previous studies were gathered through Google Scholar search engine and Maynooth University LibrarySearch, a catalogue system composed of diverse databases including ACM Digital Library, IEEE xplore, Scopus, among other A to Z databases

[61]. The string ("agricultural data" OR agri-data) AND ("data quality" OR "quality of data") AND (challenges OR barrier OR problems) was employed as a search query across all fields within the academic papers, resulting in 352 retrieved studies by June 2025. The eligibility criteria to select relevant evidence included:

- Peer-reviewed studies documented in English, which is a common language among the authors.
- Studies discussing the barriers, challenges or problems of data quality or its dimensions, such as accuracy, consistency, among other dimensions.
- Studies within industry 4.0 and the agricultural context.

The exclusion criteria involved removing (53) duplicates, (179) non-relevant articles through title/abstract screening, (24) purely technical and mathematical studies. The remaining 96 full-text studies were assessed based on the objective to answer the research question of this study. In total 42 studies were included in the review for this study. The reviewed papers are [2], [3], [5], [6], [8], [9], [11 - 16], [19], [21], [25], [27 – 31], [33 – 36], [38], [39], [43 – 50], [52 – 54], [56 – 59], [62] and the findings were synthesised and presented in the following section.

IV. Findings

Previous studies have emphasised the impact that DQ has on other activities, such as machine learning [20, 24, 39] and decision-making [51]. However, when analysing which precedents are causing DQ issues, it is a more intricate scenario [30]. The reason is that issues impacting DQ are not often made explicit [28]. In addition, DQ is also referred to as a multidisciplinary problem [15]. As a result, the findings from the literature review are synthesised to classify the multifaceted challenges impacting agricultural DQ. Figure 1 illustrates those challenges.

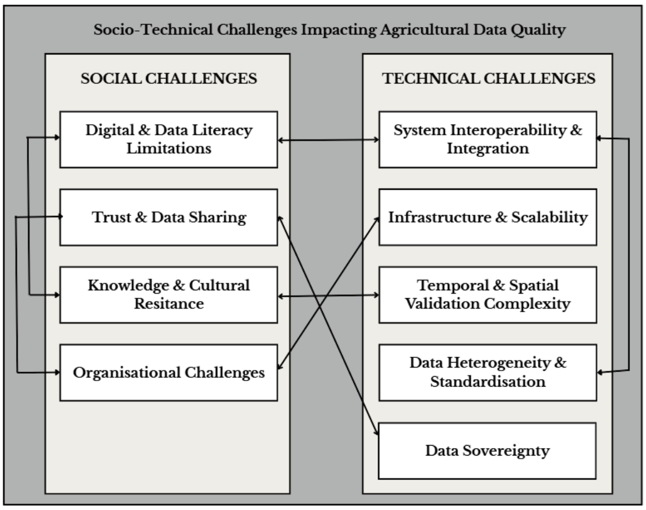

Fig. 1. Socio-Technical Challenges Impacting Agricultural Data Quality

A) Social Challenges

Digital and Data Literacy Limitations: Disparities exist in farmers' ability to effectively engage with novel smart farming technologies, which pose challenges to DQ [2, 9]. In some countries, age emerges as a key factor, with farmers being on average 55 years old and less familiar with IoT devices, expressing less confidence in digital system use and data management practices [13, 58]. The fast technological advancement in smart farming has created a situation where farmers are expected to become "data managers" without adequate preparation or training. Moreover, the study [14] argues that for dealing with agri-data, individuals, such as employees in agricultural technology organisations need broad-based skill sets regarding agricultural statistics. Although several efforts are made, they are still not good enough as rapid changes and demands occur [2]. Consequently, not having a proper understanding and skills for dealing with agri-data also increases the risk of bias at several levels and causes low data accuracy [46]. Thereby, the digital and data literacy gap directly impacts DQ through improper system use, inadequate validation practices and poor data management protocols.

Trust and Data Sharing: Trust is a critical factor affecting farmers' willingness to share agri-data [19]. Farmers demonstrate reservations about data sharing due to fears of commercial exploitation [13] derived from unclear data rights, regulatory uncertainties and potential competitive disadvantages [35, 48]. These concerns make farmers more likely to withhold agri-data, especially related to yield performance and chemical applications [35]. Nevertheless, confining data to silos does not provide representative value [11], whereas aggregated data shows more accurate and reliable scenarios [28]. For example, an individual farm provides pest data with limited location insights, while aggregated regional data from multiple farms reveals comprehensive patterns, enabling accurate forecasting and effective coordinated pest management strategies. As a result, without data sharing, DQ is impacted [3, 49], as well as having potential negative effects for neighbouring farmers.

Knowledge and Cultural Resistance: Knowledge and traditional on-farm manual recordkeeping to overcome lack of connectivity in rural areas [62] often conflict with data-driven approaches by creating cultural barriers to DQ maintenance [58]. According to [62], resistance to new data-driven practices stems from legitimate concerns about devaluing experiential knowledge and traditions accumulated over generations. When data-driven recommendations contradict established farming knowledge, farmers face difficult decisions about which information sources to trust [9]. This tension leads to selective implementation of protocols, where farmers comply with some data collection requirements while ignoring others that conflict with traditional practices. Such selective compliance undermines overall DQ and system effectiveness, creating incomplete or biased datasets that fail to accurately represent agricultural operations.

Organisational Challenges: The organisational inertia within the agricultural sector also impacts DQ. Reference [18] argues that achieving DQ was misunderstood by companies. For many organisations, the reason was the need to just replace the current internal system [51] to collect, store and process large volumes of data (i.e., big data). Thus, not even considering the importance of cohesive strategies for dealing with stakeholders' needs and concerns [51], nor clearly describe the distribution of responsibilities and access [36, 45]. Moreover, bureaucratic processes, lack of transparency, and resource constraints also demonstrate slow adoption of DQ practices [6]. Consequently, this limits the businesses' capacity to establish, monitor, and enforce consistent DQ standards in agriculture.

B) Technical Challenges

System Interoperability and Integration: The fragmentation in agricultural IS poses a challenge for maintaining DQ [28], especially when agri-data is shared among incompatible systems, causing synchronisation failures or partial data transfers [2, 11, 36]. Whereas smart farming provides multiple solutions, they did not evolve together [3]. It means that despite organisations providing solutions to farmers, the digital systems have limited integration capabilities [47]. Moreover, the proprietary data formats worsen these integration challenges [11], particularly regarding commercial competition, which has resulted in closed data ecosystems that impede seamless data exchange. Consequently, during data sharing between proprietary systems, the quality of data degrades through inconsistencies, errors, duplications, data loss, and format-specific limitations, which altogether impact DQ [11, 21, 36, 49].

Infrastructure and Scalability: The infrastructure represents a technical challenge for agricultural DQ [3, 50]. Reference [56] underlined that data scalability remains crucial. As smart farming expands and more IoT data sources are incorporated, it becomes even harder to store, process and obtain insights from big data without overwhelming existing infrastructure [11, 3]. This challenge stems from large and heterogeneous data, which are combined with other agri-data and are validated to enable successful decision-making [21]. Nevertheless, this validation process still challenging, especially for temporal and spatial data [21, 36, 47].

Temporal and Spatial Data Validation Complexity: Considering that agricultural operations are subject to constant environmental change, the relevance of agri-data deteriorates rapidly due to the dynamic environmental conditions [12]. For instance, temperature, humidity and soil moisture factors fluctuate along the day, creating challenges for maintaining data currency and temporal validity [12]. Consequently, this scenario makes it difficult to establish appropriate validation protocols for time-sensitive agri-data [11]. The spatial heterogeneity adds another complexity layer for managing DQ [8, 14]. It means that agri-data interpretation depends on local context, with DQ standards appropriate for one region potentially being unsuitable for others due to differences in growing conditions, farming systems and technological infrastructure [14]. Accordingly, spatial variability complicates the development of universal quality metrics and validation protocols [11], requiring context-aware quality assessment frameworks.

Data Heterogeneity and Standardisation: The diverse nature of agri-data also presents technical challenges for data quality management [12, 21]. Agri-data varies among text, numbers, images and videos [2]. This heterogeneity makes it extremely difficult to apply consistent quality assessment metrics and validation procedures across different data types [30]. The lack of standardised protocols further complicates the management of agricultural DQ. Different sensors, IoT devices, and software platforms employ divergent data schemas, measurement units and temporal resolutions, hence making data integration and quality comparison technically challenging [12, 21]. Without standardised technical specifications, establishing baseline DQ metrics becomes nearly impossible [2, 6].

Data Sovereignty: It also presents challenges that impact agricultural DQ. Data Sovereignty refers to the fundamental right and capacity of individuals (i.e., farmers) and organisations to exercise independent control and autonomy over their digital presence [59]. This encompasses the digital infrastructures, the technologies employed, raw data and all forms of digital content [43, 57]. For instance, when agri-data is stored in the manufacturer's proprietary cloud system, the contextual metadata is lost [43, 57]. Therefore, farmers have no control over what metadata is captured or retained by the manufacturer's equipment and system [38]. Consequently, by losing contextual metadata, agri-data is less valuable for farm management decisions, since it impacts the data provenance and trustworthiness of the data [11, 49, 58].

V. Discussion

The socio-technical integrated perspectives aligned with STS theory provide an essential view on how people, organisational inertia, and technology impact agricultural DQ at multiple levels. Our study demonstrates how social and technical challenges are multifaceted in ways that intensify agricultural DQ problems.

Digital literacy limitations among farmers averaging 55 years old intersect with the conflict between cultural resistance and adoption of data-driven approaches [9, 62] alongside system interoperability and integration [21, 28], which are unable to address the heterogeneity of agri-data [8]. This creates cascading effects where farmers lacking digital skills [13] navigate through fragmented and incompatible systems [21] that further discourage proper DQ management [3]. Similarly, trust and data sharing challenges, wherein farmers' concerns about commercial exploitation led to data withholding [35], intersect directly with data sovereignty issues [57], where proprietary systems deprive farmers of control over their contextual agricultural metadata, generated through smart farming. In other words, farmers lose trust because they lose control [62], leading to further data withholding that degrades collective DQ.

Furthermore, the conflict between traditional knowledge practices and data-driven approaches exemplifies complex socio-technical intersections [9]. For instance, the environment dynamism renders temporal and spatial agri-data rapidly obsolete [11, 12]. However, farmers' knowledge and traditions provide context that technical systems often struggle to validate agri-data in real-time in rural areas [11, 62]. Consequently, this creates skepticism regarding the objectivity of agri-data [58]. Thereby, farmers engage in selective compliance by following some requirements while ignoring others that conflict with their knowledge, which in turn affects the consistency and reliability of agri-data.

Organisational challenges delineate misalignments among cohesive strategies [18]. Thereby, it intersects with technical capabilities, such as infrastructure and scalability [3], as well as data sovereignty [59]. In other words, the absence of holistic strategies emphasises systems replacement over stakeholder needs [18, 51]. As a result, proprietary formats are employed by organisations, hence causing market-driven fragmentation that compounds trust issues.

Notably, these challenges mutually exacerbate agricultural DQ.

VI. Limitations and Future Directions

We acknowledge the existence of certain limitations inherent in this study, which may have influenced the interpretation of the findings.

Through the rapid evolution of technologies, the identified technical challenges may further evolve quickly and be resolved, and novel challenges may also arise. New solutions addressing such as interoperability and connectivity continue to emerge, hence potentially altering the technical landscape faster than the social challenges.

Future research should assess how specific socio-technical challenges correlate with measurable quality characteristics (i.e. dimensions). Furthermore, with the Data Act regulation becoming fully applicable on the 12th of September 2025, future research should expand this study and investigate the relationship of the legal framework against DQ, since legal factors influence DQ [30] and data recipients (i.e., stakeholders) still should be granted data of high quality.

VII. Conclusion

This study reviewed 41 studies and identified nine challenges impacting agricultural DQ as per figure 1. Through an integrated perspective on socio-technical challenges aligned with STS theory, we demonstrated that agricultural DQ issues arise from complex interactions between people, organisational inertia and technology. Our framework contribution transcends challenges identification to assert that successful agricultural DQ interventions require a reconceptualisation from technical optimisation to socio-technical system design. It means that recognising effective agricultural DQ improvements requires alignment between social and technical factors rather than technical dominance.

Moreover, we emphasise that quality in data collection, validation and sharing requires time and investment in terms of financial and personal development, which may not provide immediate economic return. Therefore, without a clear understanding of the potential benefits of maintaining DQ in agriculture, stakeholders prioritise immediate operational needs over DQ maintenance activities.

This study concludes that agricultural interventions for better agricultural DQ must weigh both technological capability and social aspects equally. Additionally, contextual factors influence how challenges manifest across different agricultural settings, hence requiring context-specific and flexible approaches that consider local farming systems, technological landscapes and socio-cultural factors. By advancing to subsequent DSRM phases, this framework can evolve from a theoretical construct into a practical solution, while providing a valuable foundation for researchers, technology providers and policymakers.

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