Internet Re

More than two decades of research on IoT in agriculture: A systematic literature review

Journal:	*Internet Research*
Manuscript ID	INTR-07-2022-0559.R2
Manuscript Type:	Research Paper
Keywords:	Internet of Things (IoT), Smart Agriculture, Technology Adoption, Layered Architecture

More than two decades of research on IoT in agriculture: A systematic literature review

Abstract

Purpose – Agriculture is one sector where the Internet of Things (IoT) is expected to make a major impact. Yet, its adoption in the sector falls behind expectations. The purpose of this paper is to present the state-of-the-art of IoT in agriculture and investigate its slow adoption in the sector.

Design/methodology/approach – The authors have undertaken a systematic review and a synthesis of 1355 relevant publications over the last decade.

Findings – This literature review reveals that the "big three" barriers for the overall sector are cost, skills, and standardization. The lack of connectivity and data governance are two key reasons why most of the proposed IoT solutions are standalone systems of limited scope, while the majority of commercial IoT efforts focus on practices in the protected indoor environment. Lastly, the analysis of past research along the five layers of the IoT system architecture reveals limited attention to barriers and solutions at the business layer, which represents a research opportunity for information systems scholars.

Originality – To the best of our knowledge, this is the first comprehensive review of adoption barriers and solutions across all five layers of the IoT system architecture.

Keywords Internet of Things (IoT), Smart Agriculture, Technology Adoption, Layered Architecture

Paper type Literature review

Acknowledgement: This manuscript is a revised and expanded version of a paper entitled "IoT Adoption in Agriculture: A Systematic Review" published at the 28th Americas Conference on Information Systems, 2022.

1. Introduction

With an expected 24 billion connected devices in 2025 (GSMA Intelligence, 2021), IoT is poised to become the next big "thing" after the advent of computers, internet and smartphones, leading to the fourth industrial revolution (Kuaban *et al.*, 2019). While the majority of IoT efforts are found within the sectors of early adopters such as manufacturing (Barenkamp, 2020), the share of agriculture remains relatively modest with only 4%, as compared to manufacturing with 22% (IoT Analytics, 2020). Yet, agriculture is one of the sectors where the IoT can have a major impact, offering new capabilities for better yield production (Ruan *et al.*, 2019) while reducing input costs (Wu and Ma, 2020). Even a small improvement, as little as 7 to 9%, using IoT, would translate to $500 billion in contribution to the global GDP within the next ten years as predicted by Goedde *et al.* (2020). Economic benefits aside, the application of IoT technology in agriculture would also have a positive impact on the environment and human health by reducing the use of pesticides (Varandas *et al.*, 2020), and reducing water consumption for irrigation, where the sector currently accounts for 70% of all freshwater use globally (Khokhar, 2017).

As much as in the industry, IoT in agriculture has attracted great attention in academia with an exponential number of publications since 2015 (see Figure 1). Several studies suggest that we now seem to have all key essentials in place for IoT to function, such as low-cost sensor kit (Jaisankar *et al.*, 2020), connectivity

(Pham *et al.*, 2016) and data analytics (Kitpo *et al.*, 2019). Yet, in reality, the vast majority of the IoT ventures in agriculture are likely to remain experimental for the foreseeable future. The general consensus of scholars (Roussaki *et al.*, 2019) is that IoT has failed to deliver on the high hopes and expectations for agriculture to date due to various reasons, beginning with the cost of upfront investment (Elijah *et al.*, 2018), lack of robust connectivity (Villa-Henriksen *et al.*, 2020) and high power consumption (Nigussie *et al.*, 2020), paired with limited access to energy sources and short battery life.

While there is a growing body of literature that recognizes the lack of IoT adoption in agriculture and its related factors, the existing research still focuses on the potential benefits of IoT and the feasibility of its technical implementation. There have been only few studies with substantial coverage of adoption barriers. For example, Fodor (2020) conducted survey research involving 604 farmers investigating legal and administrative barriers in the Hungarian context, while Pivoto *et al.* (2018) ran semi-structured interviews with industry experts to understand the main barriers to the IoT adoption in Brazilian agriculture. Despite providing valuable insights, the findings of these studies are limited to the regional circumstances within which the research was conducted, and therefore have a limited generalizability. There have also been a handful of studies examining factors for the IoT adoption in agriculture, using well-known theories and models in the information systems (IS) discipline such as the Behavioral Reasoning Theory (e.g., Pillai and Sivathanu, 2020), the Technology Acceptance Model (e.g., Chuang *et al.*, 2020), the Unified Theory of Acceptance and Use of Technology Model (e.g., Ronaghi and Forouharfar, 2020), and the Diffusion of Innovation Theory (e.g., Padyab *et al.*, 2020). Nevertheless, these IT adoption theories and models (particularly TAM and its variations) are likely to be ill-fitted for studying the IoT adoption in agriculture because the sector has its own social, technical, and business challenges that are much more contextual and complex than the individual's attitude. Finally, we also found few publications that attempt to conduct a comprehensive review of research on the application of IoT in agriculture. In a well-cited literature review paper, Villa-Henriksen *et al.* (2020) reviewed 167 articles systematically, yet the review only covered arable (open-field) farming, excluding any other type of agriculture, such as greenhouse and sub-sectors like livestock. Consequently, our understanding of its adoption in the sector remains incomplete, as most studies only provide a generic overview with limited in-depth investigation.

In light of this research gap, we seek to undertake an extensive review and a synthesis of the relevant publications from the last decade, with an aim to present the state-of-the-art of IoT in agriculture and investigate its slow adoption in the sector. As a first step in this direction, we focus on the following research question:

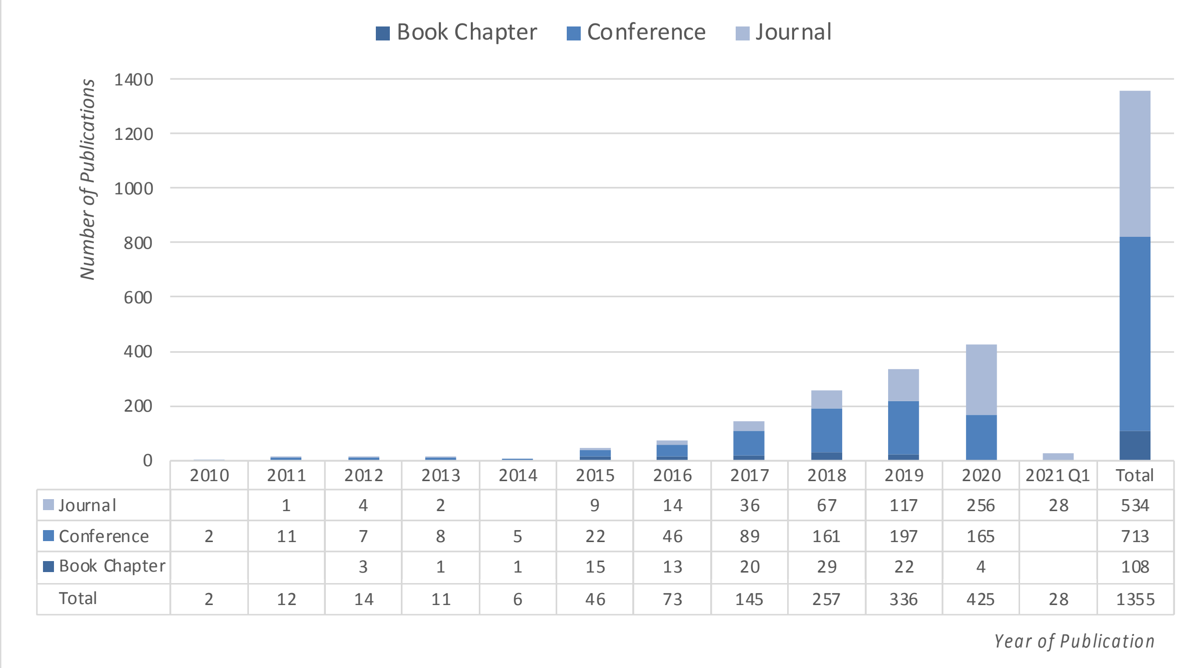
RQ1 – What are the main barriers to the adoption of IoT in agriculture identified by existing academic research?

The first RQ pertains to substantially identifying the challenges highlighted by the existing research for the lack of IoT adoption in agriculture. This will help to explore and understand the specific challenges associated with technology, region, and type (e.g., indoor versus outdoor) of agriculture, and inform the next research question:

RQ2 – What technological and managerial solutions have been proposed in academic research to address the adoption barriers of IoT in agriculture?

The second RQ aims to show how the barriers could be mitigated or overcome by some of the recent technological advancements and novel ideas and solutions proposed in academic literature. Addressing RQ2 also helps uncover gaps and shortcomings in extant research, so as to provide a direction for further research.

In the remainder of the paper, we define the scope of the research and explain the methodology of our systematic literature review. Next, we present the main findings of the review and discuss the implications. Finally, the paper concludes and provides recommendations for further research.



	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021 Q1	Total
Journal		1	4	2		9	14	36	67	117	256	28	534
Conference	2	11	7	8	5	22	46	89	161	197	165		713
Book Chapter			3	1	1	15	13	20	29	22	4		108
Total	2	12	14	11	6	46	73	145	257	336	425	28	1355

Figure 1. Publications by year

2. Internet of Things (IoT): an overview

IoT is neither an invention nor a discovery, but can rather be described as a paradigm shift (Elijah *et al.*, 2018) or a new concept (Villa-Henriksen *et al.*, 2020) based on the combined use of different technologies, mainly sensors, Internet (usually wireless) networks and data analytics. Illustrated in Figure 2, any IoT solution, regardless of the area of application, has these interdependent core components where sensors are interconnected via Internet to collect data, which can be exchanged and stored for analysis in (near) real-time (Navarro *et al.*, 2020).

Having its roots in radio-frequency identification (RFID) technology (Li *et al.*, 2016), IoT solutions from the early 2010s (e.g., Zhu and Sun, 2012) found in agriculture, were attempts to integrate RFID for identification and the tracking of agricultural products. Today, they come in a broad range in terms of structure and coverage from isolated standalone systems for a specific task, such as irrigation (e.g., Rodriguez-Robles *et al.*, 2020) and frost detection (e.g., Guillen *et al.,* 2021), to the platforms with an ecosystem with diverse stakeholders to support multiple tasks (e.g., Jaisankar *et al.*, 2020). Besides, there are advanced use cases, such as "farm-to-fork" (e.g., Mondragon *et al.*, 2020) to integrate beyond agriculture into supply chain for a sustainable and secure food chain.

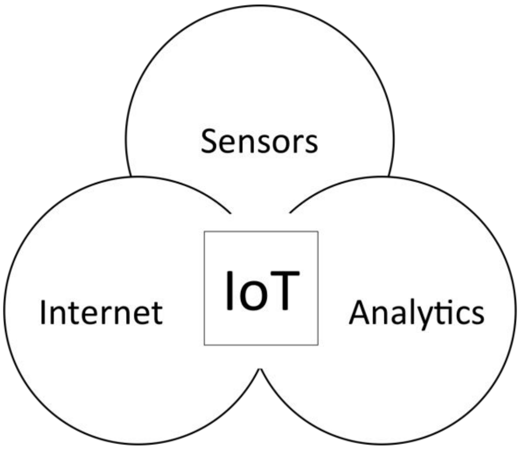


Figure 2. Core components of IoT (Grammenos and Poole, 2019)

Although there is no agreement on a standard architecture of IoT among scholars (Shi *et al.*, 2019), most of the early solutions reviewed consist of three layers (Luo *et al.*, 2016) – device, network and analytics, which are in line with the core components in Figure 2.

With the integration of complementary technologies including AI, unmanned aerial vehicles (UAVs), cloud computing and blockchain, as well as new approaches to cloud computing such as edge and fog computing, the IoT system architecture has become more granular over the years. As depicted in Figure 3, the structures of IoT systems vary, generally from three to five layers, according to the offering and chosen technology stack. For the purpose of this paper, we use the more comprehensive, five-layered architecture to categorize the key elements of the IoT system architecture.

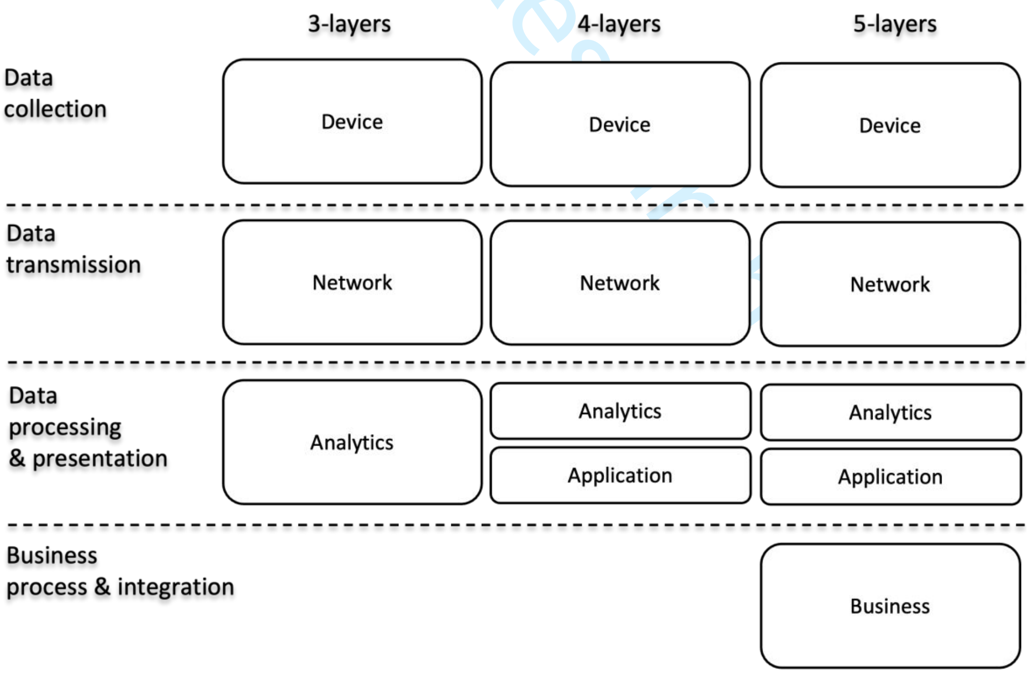


Figure 3. Proposed IoT layers – adapted from (Li *et al.*, 2016; Luo *et al.*, 2016; Trilles *et al.*, 2020)

3. Research scope and methodology

This study reviews the academic work on IoT in agriculture published in the last decade between 2010 and first quarter of 2021, following an approach adapted from vom Brocke *et al.* (2009) for search and screening. Although the literature on IoT is found predominantly within the IS field, the interdisciplinary nature of IoT research requires researchers to look beyond the field (Webster and Watson, 2002). Therefore, the search was not limited by any discipline to avoid exclusion of any valuable work. Using simple search queries applying the Boolean operators AND and OR, as many relevant items as possible were retrieved to cover all relevant terms such as “smart agriculture”, “precision agriculture”, “agricultural”, “agri-iot”, or terms that are used interchangeably like “farming”, “farmland”, etc.

As illustrated in Figure 4, the initial search running the query, e.g., ("internet of things" OR "iot") AND ("agri*" OR "farm*") on nine widely used online databases returned 3929 research items including peer-reviewed published articles, conference papers and book chapters, which have been found to contain relevant keywords in their abstract section. The output has been exported to Zotero, a bibliographic management software for management of the articles collected (Trinoskey *et al.*, 2009). As the next step, the duplicate items (including the same papers published in different formats) were removed from the combined list of items from each of these databases, reducing the total number to 2968. Further to this, reading the abstract section of each item one by one, those publications which were not published in English or had no focus on the topic of IoT in agriculture, were removed. Subsequently, 1494 items were removed leaving 1474 items shortlisted for full article reading. Another 119 items had to be removed as we had no full-text access to these. As a result, a total of 1355 publications were fully reviewed for this research.

Sample Query	("internet of things" OR "iot") AND ("agri*" OR "farm*")			
Filtered by	Year:	2010 - 2021 Q1		
	Language: Type:	English Journal article, Conference paper, Book chapter		
Databases	AISeL Emerald Insight IEEE ProQuest Sage Journals	52 332 1341 82 4	ScienceDirect Taylor & Francis Web of Science Wiley Online	287 197 1625 9
Total				3929

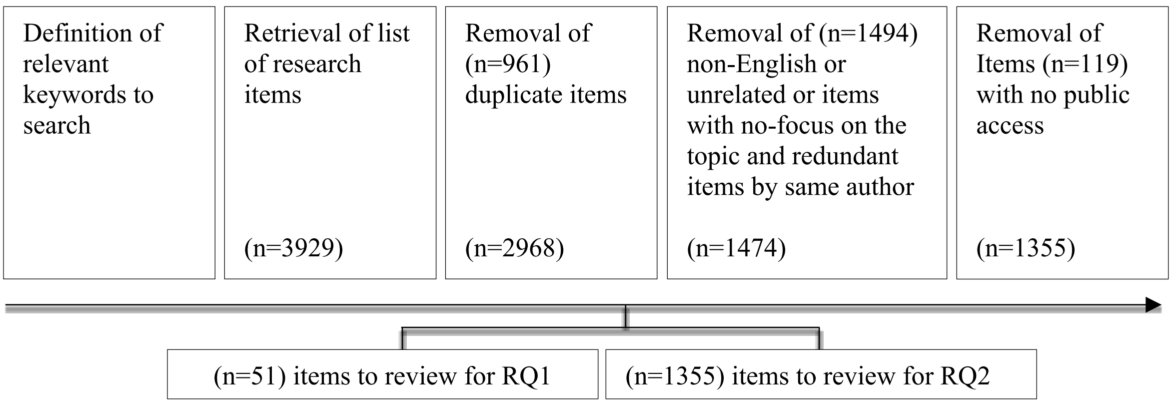


Figure 4. Search scope and screening process

With respect to the analysis, we developed an excel template to manage the coding process and to record the results. In the first step, each article was reviewed and codified. In the next step, these codes were re-organized and were assigned into themes and categories based on emerging patterns.

Regarding the analysis of barriers (RQ1), a subset of 51 studies from the collection was carefully selected based on two criteria: extent of coverage and relevance. First, the study must provide a substantial level of information and emphasis on the barriers to IoT adoption. Second, the issues or challenges reported in the study are not simply about a particular technical issue but are factors generalizable to the adoption of IoT in a wider context. We then code and categorize barriers discussed in the selected articles, using a framework adopted from Hadjimanolis (2003). Figure 5 depicts our overall framework for the literature analysis.

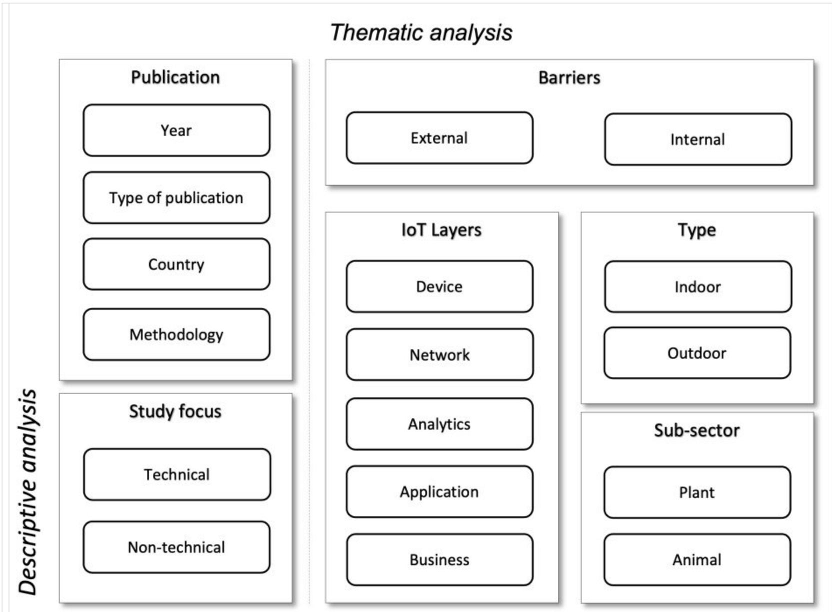


Figure 5. Conceptual framework for literature analysis

4. Findings and discussion

4.1. Descriptive analysis

The analysis of the publication years of 1355 studies from 2010 to the first quarter of 2021 indicates that agriculture has only become a domain of IoT research within the last decade. While publications on IoT started to appear in the early 2000s, the first studies related to agriculture came out in 2010. It wasn't until 2015, however, when the number of published articles saw a surge from 6 to 46 items, compared to the previous year. As illustrated in Figure 1, each year thereafter shows a steady increase over the previous year for 59% (73 items), 99% (145 items), 77% (257 items), 31% (336 items) and 26% (425 items) from 2016 to 2020, respectively. This upward trend, which is likely to continue, clearly highlights a growing interest in and the attention of researchers in IoT for agriculture.

More than half of the publications analyzed are in the form of conference papers and proceedings (53%, 713 items) that are mainly derived from IEEE database, followed by journal articles (39%, 534 items) and book chapters (8%, 108 items). A vast majority of them are notably technical in nature (94%, 1280 items). As shown in Figure 6, the number of non-technical studies (10%, 134 items) barely exceeds 10% of all publications since 2015. These are the items that cover non-technical aspects such as business modelling, value proposition and user adoption. Publications having elements with equal weight on both sides, technical and non-technical, are included in both categories.

In terms of research methodology, the majority of analyzed studies adopted a quantitative approach. Experiment (43%, 578 items) came out as the most popular methodology employed, mainly by studies with a technical focus, to test the applicability of the proposed solution at home, in a lab or campus environment, while fewer authors had a chance to experiment in the field under real-world setting (only 13%, 176 items). Prototype (13%, 182 items) and simulation (8%, 107 items) are two other methodologies with significant use. Literature review (18%, 248 items) is the second most favored methodology overall, while being the most preferred one for studies with non-technical focus, followed by case study (3%, 35 items) and survey (0.7%, 10 items).

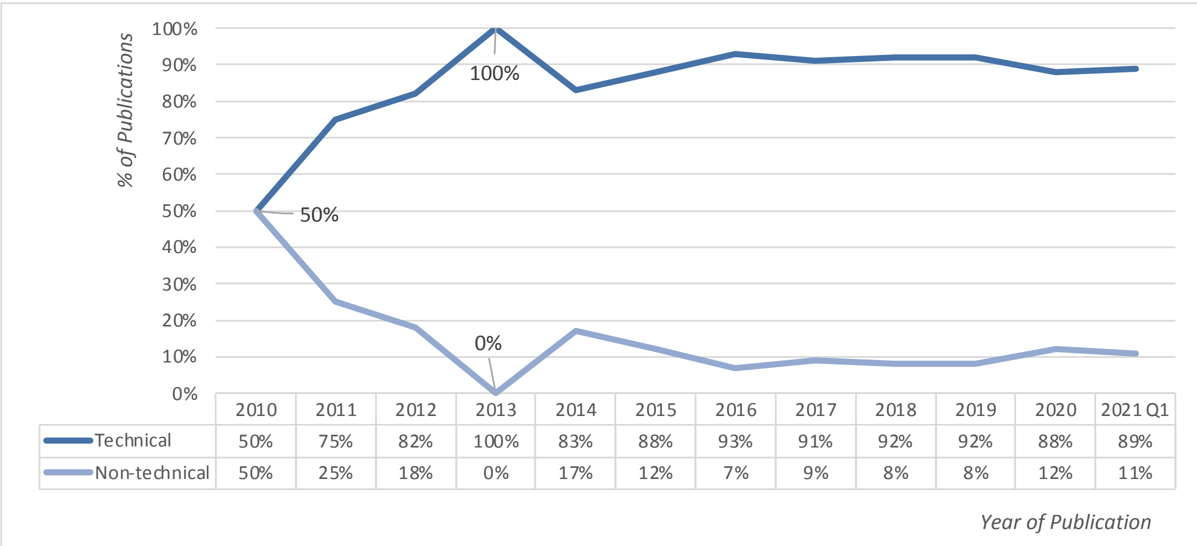


Figure 6. Publications by focus

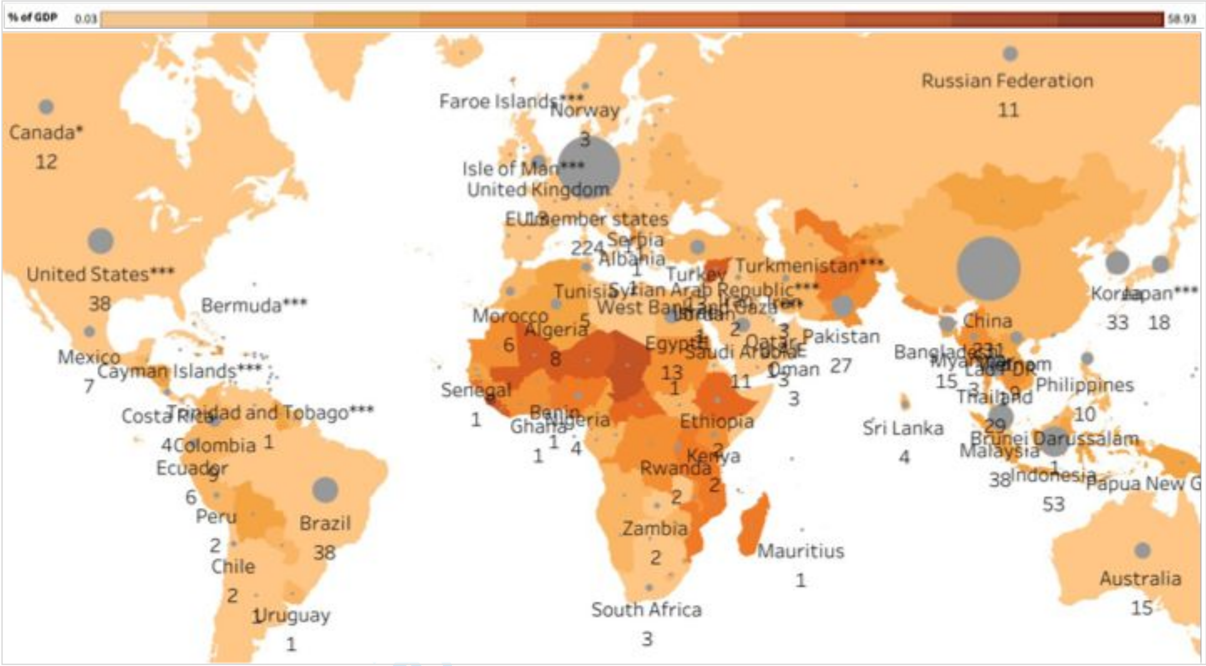
Table I provides a summary of the distribution of studies by methodology and study focus area. A closer inspection of the table will reveal a significant scarcity of empirical research found within non-technical studies, where only 3% (37 items) of all publications provide some sort of empirical evidence.

Table I. Publications by research methodology

Methodology	*Non-technical*	*Technical*	*Mix*	Total
Experiment (home/lab/campus)	-	577	-	577
Literature Review	50	164	34	248
Prototype / Model	2	173	7	182
Field Experiment	3	170	3	176
Simulation	-	106	1	107
Mixed Methods	4	9	4	17
- Experiment (home/lab/campus)	-	6	1	7
- Field Experiment	1	6	2	9
- Survey	1	1	2	4
- Focus Group Interview	1	-	-	1
- Literature Review	-	-	1	1
- Case Study	1	1	1	3
- Semi-structured (Expert) Interview	1	-	1	2
- Multiple-case study	1	-	1	2
- Prototype	-	2	-	2
- Simulation	-	1	-	1
- Workshop	1	-	-	1
Case Study	3	24	8	35
Survey	9	-	1	10
Semi-structured Expert Interview	1	-	1	2
Social Media Data Analysis	1	-	-	1

The analysis of the geographical distribution of the publications indicates that about 60% (816 items) of all publications originate from India, China, and the EU, combined. India (27%, 361 items), where the agricultural sector plays a vital role in the country's economy, contributes the most, followed by China (17%, 231 items). Indonesia (4%, 53 items), Pakistan (2%, 27 items), and Bangladesh (1%, 15 items) are other noteworthy contributors among the emerging economies with considerable dependence on agriculture. The level of economic dependency of countries on the sector along with their contribution to the IoT research has been illustrated in Figure 7, where the affiliation of the first author is used to determine the origin of the item.

Taken together, the distribution of the publications by geography and by year reveals that most early studies up to 2015 originate from China, partly as a result of conscious political determination. The Chinese government has been actively promoting research and development of IoT to accelerate the modernization of rural agriculture as a part of its Internet Plus initiative (Xiang and Wang, 2020). The EU is the other public champion of the early IoT research represented by 23 member states in the analysis, with a significant contribution from Italy (3.3%, 46 items), Spain (2.7%, 37 items), Greece (1.7%, 24 items), Romania (1.6%, 21 items), and Portugal (1.5%, 20 items). Many of these studies were produced between 2014 and 2020 as a result of EU-funded research projects backed by the EU's Horizon 2020 initiative (Roussaki *et al.*, 2019).



Country	No. of publications										
India	361	Japan	18	Algeria	8	Iran	3	Slovenia	2	Montenegro	1
China	231	Australia	15	Germany	7	Myanmar	3	Zambia	2	New Zealand	1
Indonesia	53	Bangladesh	15	Mexico	7	Norway	3	Albania	1	North Macedonia	1
Italy	46	France	14	Ecuador	6	Oman	3	Argentina	1	P.N.A.	1
Brazil	38	Egypt	13	Morocco	6	South Africa	3	Benin	1	Qatar	1
Malaysia	38	Ireland	13	Austria	5	U.A.E.	3	Brunei	1	Senegal	1
U.S.A.	38	Turkey	13	Tunisia	5	Chile	2	Bulgaria	1	Serbia	1
Spain	37	U.K.	13	Costa Rica	4	Cyprus	2	Croatia	1	Sudan	1
Taiwan	35	Canada	12	Finland	4	Czechia	2	Ghana	1	Sweden	1
South Korea	33	Russia	11	Hungary	4	Ethiopia	2	Israel	1	Trinidad and Tobago	1
Thailand	29	Saudi Arabia	11	Netherlands	4	Iraq	2	Jordan	1	Uruguay	1
Pakistan	27	Philippines	10	Nigeria	4	Kenya	2	Laos	1		
Greece	24	Belgium	9	Singapore	4	Peru	2	Latvia	1		
Romania	21	Colombia	9	Sri Lanka	4	Poland	2	Lithuania	1		
Portugal	20	Vietnam	9	Denmark	3	Rwanda	2	Mauritius	1		

Figure 7. Countries by number of publications versus share of agriculture, forestry, and fishing in GDP (%) for 2020 (World Bank, 2021)[1]

Notes: * GDP from 2017, ** GDP from 2018, *** GDP from 2019

4.2. Thematic analysis

4.2.1. Barriers to IoT adoption in agriculture (RQ1)

The barriers to the adoption of IoT in agriculture are numerous and diverse. For a better overview and understanding of the identified barriers, our coding process follows a mix of inductive and deductive approaches for the categorization of the results from the analysis of 51 selected publications. Each article is reviewed, and is coded to identify the barriers (e.g., equipment) and to assign them into themes (e.g., availability) using an inductive bottom-up approach. A deductive top-down approach is then used to apply a taxonomy adopted from Hadjimanolis (2003), to assign them into further top-level categories (e.g., market-related under external barriers). Figure 8 provides a summary of seven main barrier categories which are broadly classified as external and internal,

[1] For interactive full version, visit http://www.cevdetbulut.com/2021-phdconf.html

and further divided into themes, and ranked according to the frequency of appearance in the coding.

While the majority (59%, 30 items) of the 51 publications recognize both external and internal barriers, there is no single study reporting on internal barriers alone. The extent of the external barriers clearly outweighs that of the internal barriers in terms of the number of factors hampering the IoT adoption in agriculture.

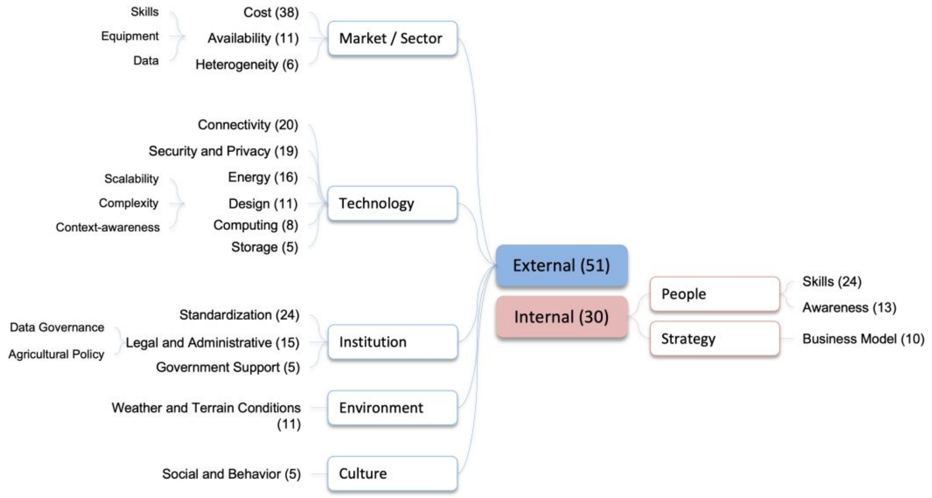


Figure 8. Taxonomy of barriers to IoT adoption

Barriers are analyzed considering the context of the study in which they were investigated, that is, region, type (indoor versus outdoor) and sub-sector (plant versus animal) of agriculture, as well as for their impact on the IoT layers (Figure 9). The fact that most of the identified barriers are interlinked requires further analysis of relationships among them (Table II). For example, while the influence is one-way (→) between some barriers, e.g., environmental conditions contribute to those barriers by increasing cost, connectivity, and energy consumption, the influence between some other barriers is running in both directions (← →), e.g., between energy and the barriers such as cost, connectivity, and computing, creating a trade-off relationship that often requires complex decision-making.

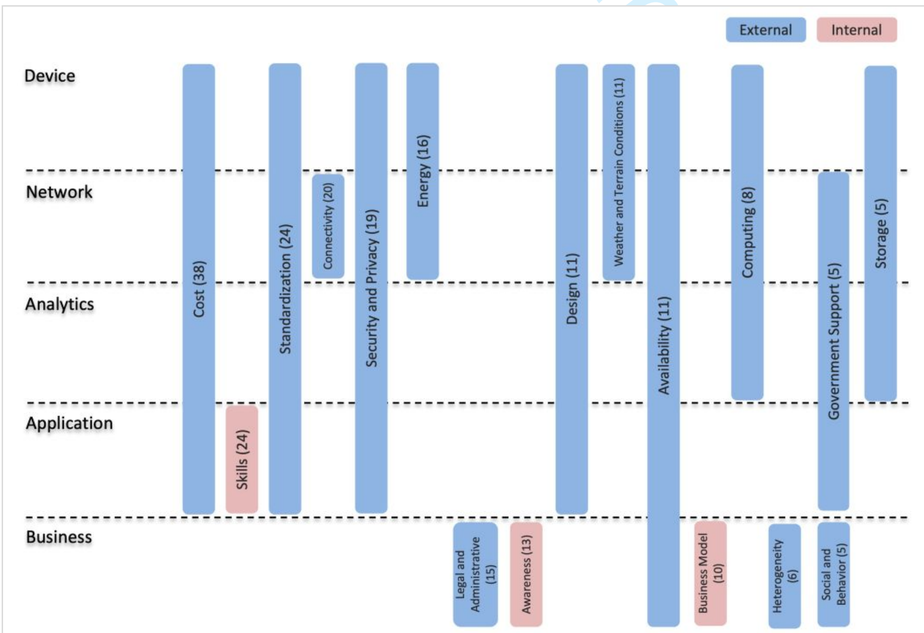


Figure 9. Barriers by IoT layer

Table II. Relationship matrix of barriers

	Availability	*Awareness*	*Business Model*	*Computing*	*Connectivity*	*Cost*	*Culture*	*Design*	*Energy*	*Environment*	*Government Support*	*Heterogeneity*	*Legal and Administrative*	*Security and Privacy*	*Skills*	*Standardization*	*Storage*
Availability			EQ→ DA→ TE→	EQ→	EQ→			EQ/SL→ DA/SL→ TE/SL→	EQ→			←EQ ←DA ←TE	←DG/DA			←EQ	EQ→
Awareness			→								←						
Business Model	←EQ ←DA ←TE	←		←	←	←	←	←CL ←SL ←TE	←	←	←	←	←DG	←	←	←	←
Computing	←EQ		→			← →		←SL→	← →					←			
Connectivity	←EQ		→			← →		←SL→	← →	←	←			← →		←	
Cost			→	← →	← →			←SL→	← →	←	←	←		← →			← →
Culture			→										DG→		→		
Design	←EQ/SL ←DA/SL ←TE/SL		CL→ SL→ TE→	←SL→	←SL→	←SL→			←SL→			←SL		←CL→	←CL→	←SL	←SL→
Energy	←EQ		→	← →	← →	← →		←SL→		←				← →			
Environment			→		→	→			→								
Government Support		→	→		→	→									→		
Heterogeneity	EQ→ DA→ TE→		→			→		SL→								→	
Legal and Administrative	DG/DA→		DG→									←DG		←DG→			
Security and Privacy			→	→	← →	← →		←CL→	← →				←DG→		←		→
Skills			→				←	←CL→			←			→			
Standardization	EQ→		→		→			SL→				←					
Storage	←EQ		→			← →		←SL→						←			

Legend

→	Direction of impact
← →	impact two ways (trade-off relation)

Abbreviations

CL	Complexity
DA	Availability of Data
DG	Data Governance
EQ	Availability of Equipment
SL	Scalability
TE	Availability of Technical Expertise

4.2.1.1. Market/ Sector related

Among the market related barriers, cost (75%, 38 items) has been cited as the leading factor, followed by lack of availability (22%, 11 items) and heterogeneity of agriculture (12%, 6 items). As illustrated in Figure 9, it impacts across multiple IoT layers, including the device layer, e.g., the cost of sensor equipment (Jaisankar *et al.*, 2020), the network layer, e.g., expensive connectivity (Kuaban *et al.*, 2019), the analytics and the application layers, e.g., cost of cloud services (Villa-Henriksen *et al.*, 2020).

When it comes to the root of the cost as a barrier, however, our analysis indicates that there are different underlying rationales depending on the research context. For example, the research in the context of low-income economies tend to treat it as a matter of affordability, underlining the low purchasing power of farmers as a prohibiting factor for the adoption of IoT, e.g., in Sub-Saharan Africa (Pham *et al.*, 2016) and in India (Pillai and Sivathanu, 2020). In the context of upper-middle- and high-income economies on the other hand, the cost is an equally concerning factor for the wealthy farmers, but the reason being lack of return of investment (ROI). Low commodity prices, e.g., in China (Xiang and Wang, 2020) or the small holding sizes, e.g., in Hungary (Fodor, 2020) won't justify an investment for IoT technology. Consequently, the majority of commercial efforts remain limited to "high value" commodities. As for plants, these mainly include grapevine (e.g., Trilles *et al.*, 2020), coffee bean (e.g., Sales *et al.*, 2020) and olive (e.g., Varandas *et al.*, 2020). With regard to animals, the commercial applications are largely being reported for fisheries (e.g., Hang *et al.*, 2020) and livestock (e.g., Ma *et al.*, 2020). It is finally worth mentioning that there is often a complex trade-off decision-making between cost and other barriers related to connectivity, energy, computing, storage, design parameters and security measures as shown in Table II.

The limited availability (22%, 11 items) of hardware equipment, technical expertise and data are other market related barriers with an impact felt across all IoT layers, as well as types and sub-sectors of agriculture. IoT equipment such as sensors are either not at all available for sale (Kour and Arora, 2020) or not yet mature enough (Villa-Henriksen *et al.*, 2020) to support a reliable service for agriculture. Additionally, there is a further lack of technical skills and expertise reported in the context of developing countries to implement and support the IoT solution on the ground (Kuaban *et al.*, 2019). Other studies report a lack of availability of high-quality and open data (e.g., Xiang and Wang, 2020) in the sector. Lack of availability also impacts other barriers related to connectivity, energy, computing, storage, and scalability under design barriers.

The heterogeneous nature of agriculture (12%, 6 items) is another prominent market related barrier in the literature. Researchers found that the amount and diversity of processes and stakeholders in the sector (Verdouw *et al.*, 2019) make it almost impractical to develop a single solution or business model (Brewster *et al.*, 2017) that would work for different regions, types and sub-sectors of agriculture. Heterogeneity is found as a determinant factor that has impact on other barriers, for example, by increasing cost of IoT solutions and the need for common standards.

4.2.1.2. Technology related

Technical barriers make up the second largest group of publications, led by connectivity (39%, 20 items). This is rather a surprising result of the analysis, given the immense progress seen in mobile and wireless network technologies in recent years. Nearly all analyzed studies worldwide covering connectivity issues in the network layer still highlight the lack of reliable connectivity as the primary factor for the slow diffusion of the IoT technology in the context of rural agriculture (Lezoche *et al.*, 2020). Connectivity also contributes to other barriers, for example, by increasing the cost and energy consumption and by creating security and design challenges.

Security and privacy (37%, 19 items) are two major technical barriers that are often found associated with each other. In addition to the vulnerability of sensors and network equipment to physical attacks (Tzounis *et al.*, 2017), past research had identified the threat to the integrity and confidentiality of data (Yang *et al.*, 2021) while data circulate across multiple IoT layers: collection in the device layer, transmission in the network layer, processing in the analytics layer and utilization in the application layer (Li *et al.*, 2016). Our analysis shows no difference in perception of the security and privacy threats among the farmers in respect to the region and sub-sector of agriculture. Compared to the indoor or protected agriculture in the form of green- or glasshouse, however, the outdoor agriculture is more exposed to theft and vandalism, since sensors and some of the network equipment are visible and within reach with no surveillance (Tzounis *et al.*, 2017). Security and privacy measures often create difficult trade-offs to other barriers related to cost, connectivity, and complexity under design barriers as well as data governance under legal and administrative barriers.

Energy (31%, 16 items) is a significant barrier due to use of conventional energy sources (Kour and Arora, 2020) with a limited lifetime such as battery in the device and network layers. Energy consumption is confirmed as a challenge, regardless of the region and sub-sector of agriculture by the studies and highlighted particularly in the context of outdoor agriculture (Ruan *et al.*, 2019). Several battery-powered wireless sensors and network nodes must be deployed to cover large scale open fields, which increases cost of energy (Kuaban *et al.*, 2019) and efforts for the maintenance (Shi *et al.*, 2019). There is often a trade-off between energy and other barriers related to cost, connectivity, computing, storage, and scalability under design parameters.

The design (22%, 11 items) of an IoT solution, which encompasses a set of critical choices in terms of scalability, complexity, and context-awareness, may constitute a barrier that impacts multiple layers. The scalability barrier may manifest at the device layer (e.g., sensor nodes), the network layer (e.g., gateways and protocols), and the analytics and application layers (e.g., cloud storage and processing). Illustrated in Table II, this often involves trade-off decisions against other barriers related to cost, connectivity, energy, storage, and computing. The complexity barrier, on the other hand, relates to the usability and ease-of-use of an IoT solution which may lead to a barrier among the end users (Pillai and Sivathanu, 2020). It is noteworthy that, perhaps contrary to prevalent expectations, no evidence was found in the literature regarding the correlation between the complexity expectations of farmers and their skills or level of education. That is, end users simply expect ready-made solutions (O'Grady and O'Hare, 2017) that provide them with easy-to-read analytics (Pivoto *et al.*, 2018). For that very reason, a trade-off must usually come into balance between the level of complexity and the level of security measures and the tech-savviness of end users. Context-awareness is the final design challenge captured in the analysis that pertains to the flexibility and adaptability of IoT solutions to the local context where it gets deployed using meta data of the surroundings (Villa-Henriksen *et al.*, 2020).

Despite the lesser extent, lack of computing power (16%, 8 items) and lack of storage (10%, 5 items) are two final technical barriers that appear in the analysis. These still pose a challenge in the device, network, and analytics layers where data storage and processing must be done locally using constrained resources, rather than remotely using cloud services (Nigussie *et al.*, 2020) due to limited or non-existent connectivity in rural areas with poor infrastructure (Pivoto *et al.*, 2018), or too expensive to justify an investment (Brewster *et al.*, 2017).

Also, there is an obvious trade-off relation to other barriers as they may lead to the increase of cost and the limitation of scalability under design barriers.

4.2.1.3. Institution related

Institutional barriers are extensively covered in the literature, led by the discussion on standardization (47%, 24 items), which came out as the third most cited barrier overall in the analysis. While early studies (e.g., Wang and Yang, 2014) identify the lack of standardization as the barrier to the IoT development, more recent studies (e.g., Brewster *et al.*, 2017) ironically point out the emergence of too many standards as a barrier underlining the need for institutional leadership to create global open standards (Shi *et al.*, 2019). The lack of standardization is a common challenge across regions, types, and sub-sectors of agriculture, and found to impact other barriers related to interoperable connectivity, the availability of compatible IoT equipment and data, as well as scalability under design barriers.

Most studies covering legal and administrative barriers (29%, 15 items) highlight the lack of data governance as a barrier to IoT adoption in the sector. The heterogeneous nature of agriculture requires market participants to collaborate (Barenkamp, 2020), which is of vital importance to the survival of any large-scale IoT implementation in any context. For instance, empirical evidence shows that farmers from India (e.g., Pillai and Sivathanu, 2020) and China (e.g., Xiang and Wang, 2020) are reluctant to adopt IoT, due to concerns about the misuse of their IoT data by service providers to gain a competitive advantage. The lack of data governance also contributes to the lack of availability of high-quality and rich data as a result of mistrust among stakeholders who may not be willing to share the data they possess (Xiang and Wang, 2020). Other barrier in this category, mentioned only by Fodor (2020), is the unfavorable regulatory environment and policies for agriculture such as limited or short-term land use rights that makes it difficult for farmers to justify a long-term investment for IoT.

The role of government is generally seen as an enabler in the diffusion of technology (Wang *et al.*, 2019). However, the lack of government support (10%, 5 items) is perceived by some scholars as a barrier, in particular to the initial stage of development of IoT (Wu and Ma, 2020) in developing countries (Shi *et al.*, 2019). In these contexts, government support is essential for building the required infrastructure, as well as for promoting IoT in agriculture by increasing awareness among farmers through workshops and trainings (Takagi *et al.*, 2021).

4.2.1.4. Environment related

Difficult environment and terrain conditions (22%, 11 items) can be detrimental to the development of IoT in agriculture. Device and network are two affected layers as the IoT equipment is exposed to the extreme weather conditions that can lead to sensor and communication failures (Villa-Henriksen *et al.*, 2020). Besides being reported as a barrier, mainly to the outdoor agriculture in regions with harsh environment, it is also found to contribute to other barriers related to cost, connectivity, and energy.

4.2.1.5. Culture related

Despite being covered by a relatively small number of publications, the results of analysis indicate that the culture related barriers (10%, 5 items) may well lead to low acceptance of IoT in agriculture. These consist of highly context-driven societal and behavioral factors (Lezoche *et al.*, 2020) that result in, for example, risk avoidance (Ronaghi and Forouharfar, 2020), the resistance to change due to work habits (Brewster *et al.*, 2017) and inertia (Sharma *et al.*, 2021) among the farmers. Cultural barriers can contribute to other barriers such as the lack of data governance due to uncooperative culture among stakeholders (Xiang and Wang, 2020).

4.2.1.6. People related

With regard to people related barriers, there are two challenges that surfaced in the analysis – the lack of skills (47%, 24 items) and the lack of awareness (25%, 13 items). The former makes the second most cited barrier overall. Empirical evidence shows that the current IoT solutions tend to exceed the level of understanding and technical skills of farmers (Pillai and Sivathanu, 2020), who are expected to interact with IoT solutions in the application layer. This is a barrier to the adoption of IoT particularly in the traditional rural agriculture across regions and sub-sectors. Demographic characteristics of farmers such as age and education are likely to be the underlying reason. With the continuing trend of young adults moving to cities, agriculture has become a sector increasingly reliant on older adults. This implies consequences for innovation in the sector, as shown in the example by Pivoto *et al.* (2018), who underlines the lack of skills as a barrier, due to the low level of education of landlords, of whom 27% are illiterate and only 53% have an elementary degree. Therefore, the low-skill barrier might exacerbate the technical barrier related to the complexity of design in IoT solutions. The lack of awareness is the other people-related barrier often being reported in conjunction with the skills barrier. However, we argue that this is a challenge closer to the business layer as the farmers – despite their skill level – may not be aware of the availability and potential benefits of IoT technology in the first place (Wu and Ma, 2020).

4.2.1.7. Strategy related

A small number of studies (20%, 10 items) recognize the lack of IoT-based business model as a barrier to the adoption of IoT in the sector. Many current IoT initiatives in agriculture are funded and pushed forward by the public sector entities worldwide, as shown in the descriptive analysis of this study. While acknowledging the role of the government in supporting and promoting the IoT development in agriculture (Shi *et al.*, 2019), some scholars (e.g., Wu and Ma, 2020) consider this public-funding model of development unsustainable in the long run. In the end, it is the private sector entities and entrepreneurs who will need to come up with new IoT-based business models for agriculture with a well-thought-out strategy, to convince the farmers to buy the product or pay for the service. The literature indicates that the lack of business model is a common challenge across regions and sub-sectors, and probably the only one that is impacted by all the other barriers, as depicted in Table II.

4.2.2. IoT research in agriculture: State of the art (RQ2)

Having identified the barriers to the adoption of IoT in agriculture, this section of the study attempts to answer the question: what technological and managerial solutions have been proposed in academic research to address the adoption barriers of IoT in agriculture? The analysis of 1355 publications is presented according to the focus of the research in terms of IoT layers, while considering three aspects of empirical context in the research: region, type (indoor versus outdoor) and sub-sector (plant versus animal) of agriculture.

The results of analysis by IoT layer indicate that the IoT research in agriculture accumulates around the first four layers. This is not a surprising outcome given the low number of studies covering the non-technical aspects of the subject, as noted in the preceding section. Illustrated in Table III, the network and analytics are two layers covered most frequently in the literature.

Table III. Publications by IoT layer

Layer	*No. of publications*
Device	955
Network	1060
Analytics	1033
Application	891
Business	90

4.2.2.1. Device layer

The device layer (70%, 955 items) consists of "things" that capture data from the surroundings by means of sensors or devices equipped with sensors, which may also be able to act in a capacity to perform as actuators (Navarro *et al.*, 2020). Several studies report novel approaches in the device layer, mainly due to recent technological advances in nanotechnology and robotics that may help to address some of the barriers identified. For example, Pasquale *et al.* (2019) created low-cost paper-based sensors of sustainable and eco-friendly material. In response to energy consumption, many studies discuss the feasibility of moving from conventional energy sources to self-charging sensor nodes using popular renewable energy sources such as solar energy (e.g., Varandas *et al.*, 2020).

The analysis of studies covering the device layer point out an increase of the role of UAVs and robotics in IoT, as shown in Figure 10, which are found to a large extent within outdoor agriculture for crop production to cover activities starting with data collection, e.g., for detection of water stress (e.g., Yang *et al.*, 2020). The key advantage of UAVs and robotic devices over static sensor networks is mobility, which would lead to significant cost savings by removing the need for deployment of multiple sensors to cover a large area.

4.2.2.2. Network layer

The network layer (78%, 1060 items) refers to infrastructure to facilitate two-way communication between device and analytics layer (Navarro *et al.*, 2020), has become the focal subject of many research studies. The field has moved from early IoT solutions (e.g., Zhu and Sun, 2012) consisting of three-layered architecture using wired and wireless short-range, low-rate communication technologies to solutions based on new wireless communication technologies and novel network architecture designs and topologies. These improvements may be able to address some of the aforementioned barriers in the network layer. For example, Pham *et al.* (2016) deployed a low-cost IoT solution using long range (LoRa) in the rural sub-Saharan African context and recommend it as a viable economical option for small and medium size holdings in developing countries with low infrastructure. Among the cellular wireless technologies, 3G and 4G are reported to consume high energy and have poor coverage in rural regions (Valecce *et al.*, 2020). Experimented by Guo (2021) for crop health monitoring, 5G delivers promising results for rural outdoor agriculture, as it provides wide coverage with high spectrum efficiency and low energy consumption. However, currently it seems to be a less preferable option for agriculture due to the high cost for the connectivity (Tang *et al.*, 2021).

Several recent studies investigate novel network architectures such as edge or fog computing that may allow the mitigation of impact of barriers related to connectivity, environment, energy, and scalability by reducing the network load, due to local storage and processing of data at edge level (Guillen *et al.*, 2021). There are also opportunities for better connectivity and energy savings, due to the optimization of network topology such as circular topology (e.g., Sales *et al.*, 2020).

Another example to highlight in the network layer is the emergence of underground networks where wireless devices are directly put inside the soil (e.g. Salam *et al.*, 2019). Besides protecting the network devices from hostile weather conditions, this approach could also help to reduce the risks of theft and vandalism.

Finally, a few studies covering the network layer discuss the applicability of blockchain technology to address barriers related to security and privacy. For example, Nesarani *et al.* (2020) propose using blockchain-based authentication to prevent the participation of fake nodes in a network setup for rice field monitoring.

4.2.2.3. Analytics layer

The analytics layer (76%, 1033 items) represents the heart of an IoT system since the added value of an IoT product is often built here, by storing, processing and analyzing the collected IoT data (Tzounis *et al.*, 2017) for automation, decision making and other operational support (Navarro *et al.*, 2020). Cloud computing enabled IoT solutions to provide access to abundant and ubiquitous resources such as storage and processing power, allowing advanced modeling with a high volume of data that could not be done before. Coupled with analytics and machine learning, cloud-based IoT solutions are capable of covering the full cycle of crop production, from assessing land suitability for cultivation (e.g., Vincent *et al.*, 2019), to detecting pests (e.g., Varandas *et al.*, 2020) to predicting frost events (e.g., Guillen *et al.,* 2021).

Nevertheless, the availability of cloud services depends on reliable connectivity and affordability. Although there are workarounds (e.g., Nigussie *et al.*, 2020) to move the storage and processing of data to the edge or device level in the absence of cloud resources, these solutions largely remain far from supporting a reliable service (Guillen *et al.*, 2021). As a result, many of the aforementioned barriers in the analytics layer remain unresolved, in particular for rural agriculture or in developing countries with poor infrastructure.

Finally, the studies covering the analytics layer indicate an increase of use cases for the applicability of the blockchain technology to address barriers related to data security and privacy. A recent example in this regard is the study by Hang *et al.* (2020), who propose a blockchain-based fish farm platform using Hyperledger Fabric to provide farmers with secured storage of data that cannot be tampered with.

4.2.2.4. Application layer

The application layer (66%, 891 items) is the layer of interaction of an IoT system consisting of front- and back-end applications. Front-end applications evolved from simple LCD text display to the content-rich graphical UIs, delivered through the web and mobile based applications (e.g., Varandas *et al.*, 2020). As for back-end applications, enabled by cloud computing, the emergence of new approaches to the modular system design such as use of microservices and containers (Trilles *et al.*, 2020) in the application layer has transformed many IoT solutions from stand-alone systems into connected platforms over the years, by easing the barriers related to cost and scalability.

Nevertheless, since the cloud-enabled front- and backend applications depend on reliable internet connection, IoT solutions in regions with limited internet access are likely to remain limited by scope and function. These solutions would alternatively rely, for example, on the edge-based hybrid models for offline and real-time analysis with low volume of data (e.g., Yu and Guo, 2020).

One trend worth highlighting in the application layer is the emergence of Augmented and Mixed Reality (AR and MR) technologies, as shown in Figure 10, which takes the user interactivity to the next level, by introducing the concept of digital twin to agriculture for the mirroring of physical objects (Chukkapalli *et al.*, 2020). AR and MR may also help to address barriers related to user skills by providing a visual or immersive experience for awareness building and interactive training (Yang *et al.*, 2021).

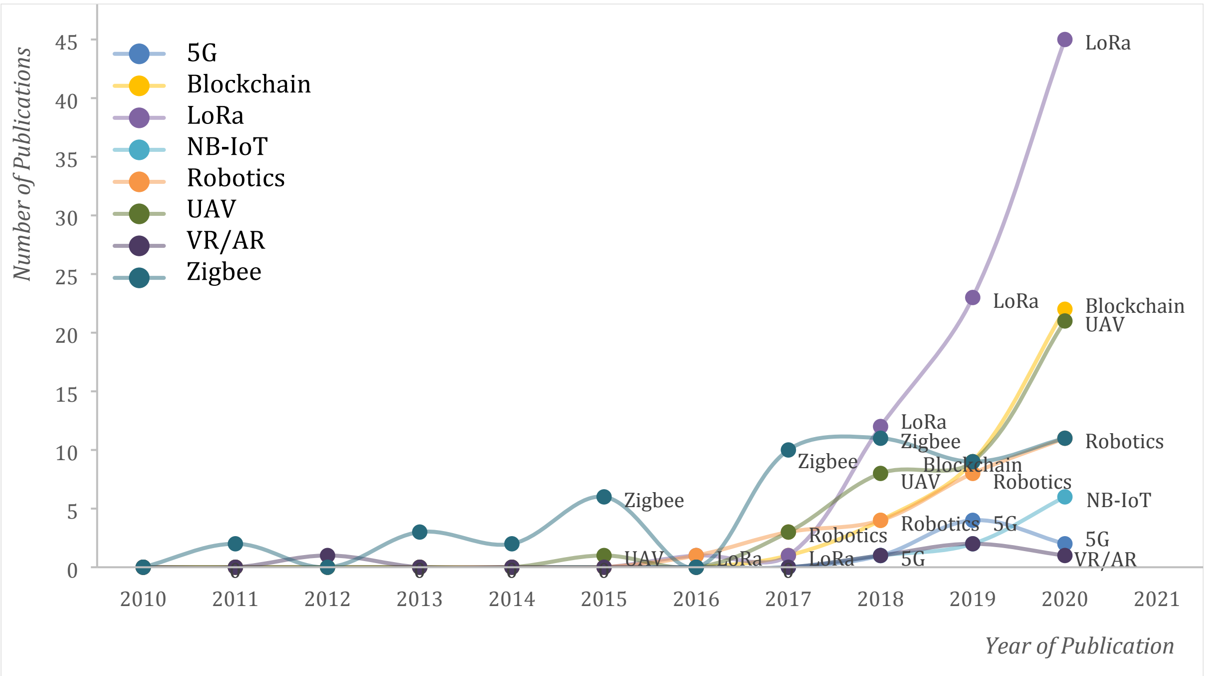


Figure 10. Publications by IoT enabling technologies highlighted

4.2.2.5. Business layer

The business layer (7%, 90 items) is the layer of management of an IoT system that involves the modeling and integration of existing business processes around a business model with a value proposition attractive to the stakeholders. Despite the relatively small number of studies found in our search, there are examples of extensive research on this front. For example, Verdouw *et al.* (2019) provide an architecture framework for modeling IoT-based systems that is applied and validated by 19 business cases for different sub-sectors of agriculture. Our analysis also reveals a highly visible public sector presence in efforts of understanding the low adoption of IoT in agriculture and developing policies and strategies for stimulating IoT development in the sector. A notable example in this regard is the WAGRI, a data platform initiative by the Japanese government to boost IoT development in agriculture, where the participating public and private sector entities are both the suppliers and consumers of the agricultural data governed under respective rules (Toriyama, 2020).

The literature also documents the emergence of new XaaS-based IoT business models for agriculture enabled by cloud computing (Rao *et al.*, 2012) such as software as a service (SaaS) model for continuous delivery and the maintenance of software at network layer (e.g., Lopez-Viana *et al.*, 2020), platform as a service (PaaS) model for cloud-based infrastructure provisioning at analytics and application layers (e.g., Barmpounakis *et al.*, 2015) and sensors as a service (Se-aaS) model for sensor provisioning at device layer (e.g., Zhang *et al.*, 2020).

Research on the value proposition typically falls under three pillars: co-operation, co-creation, and co-ownership. Co-operation refers to the collaboration between stakeholders who are incentivized through financial, environmental, and/or social benefits (Brewster *et al.*, 2017). The FIspace, for example, is a co-operation initiative by the EU, aiming to provide a platform for a seamless end-to-end integration and collaboration between public and private stakeholders in the agriculture sector (Barmpounakis *et al.*, 2015). Co-creation refers to value creation by the joint activities of stakeholders (Bidar *et al.*, 2022). Demeter, which is another initiative by the EU, is an example to highlight in this regard (Roussaki *et al.*, 2019). A multi-actor approach is proposed to support an inclusive value chain mechanism between farmers and suppliers. Lastly, co-ownership refers to the collective ownership of the cost and benefits of an IoT system by farmers (Chukkapalli *et al.*, 2020). Chukkapalli *et al.* (2020) propose value propositions based on integrating IoT into existing traditional co-op ecosystem.

5. Conclusion and future research

Through a systematic review of 1355 publications on IoT in agriculture, this paper presents the state-of-the-art research on the adoption of IoT in the agriculture sector. To the best of our knowledge, this is the first comprehensive review of adoption barriers and solutions across all five layers of the IoT system architecture, which is the key contribution of the paper. The descriptive analysis of the literature shows that the research of IoT in agriculture is a recent phenomenon within the last decade, although the interest and number of studies are rapidly growing. While India leads in the number of published studies, we highlight China's pioneering role in the IoT research for agriculture and the EU's institutional leadership in setting and driving the research agenda.

Our thematic analysis of IoT adoption studies reveals that the main barriers are cost, lack of skills, and lack of standardization. While the importance of internal and external barriers may vary depending on use context, there is no single barrier solely responsible for the slow adoption. Moreover, the findings suggest that many of the identified barriers are interlinked and often in a trade-off relationship requiring complex decision-making when designing IoT solutions. Among all identified barriers, cost, lack of standardization, heterogeneity of the sector, security and privacy, and design are found to impact across regions and sub-sectors of agriculture, while harsh environmental conditions, limited connectivity, energy, computing power and storage mainly impact the rural outdoor agriculture. On the other hand, the lack of data governance is the key barrier to any large-scale implementation and advanced IoT ecosystems such as the futuristic "farm-to-fork" use case (e.g., Mondragon *et al.*, 2020). The majority of proposed IoT solutions to date are standalone systems with limited scope and function, where irrigation is the leading application area of IoT research in agriculture.

Our analysis of research by IoT layer indicates that the network and analytics layers get most attention in the literature. This is likely due to recent technological advancements such as cloud computing, big data analytics, and low-power wide-area wireless technologies, which provide the basis for new ideas and solutions in mitigating many well-known barriers such as data storage, processing, and network connectivity. Somewhat surprisingly, our analysis shows that lack of connectivity is still a leading technical barrier to IoT implementation and adoption. The findings also suggest that, despite high expectations, the 5G technology is currently not a viable solution to the IoT connectivity problem in agriculture, due to its high cost. Consequently, the connectivity barrier becomes the primary reason why rural outdoor agriculture today is lagging behind in terms of adopting and benefiting from IoT, not only in developing countries with limited infrastructure, but worldwide. In contrast, indoor agriculture is being reported as better positioned to adopt IoT as it is likely to be less impacted by barriers related to harsh environmental conditions, connectivity, and energy. As a result, we find that the majority of commercial IoT efforts in agriculture today remain either limited to the agricultural practices under the protected indoor environment or the production of "high value" commodities such as vinery, fishery, and livestock.

This literature survey reveals several significant knowledge gaps that could be addressed by future research. First, the IoT research in agriculture is heavily technical, focusing on the technological feasibility of IoT and fundamental technical challenges in the sector while paying considerably less attention to the human, social, and cultural factors. Second, despite the high number of technical studies, there are few studies reporting large-scale field observations. Many of the reviewed studies use methods such as experiment, prototype and simulation providing limited real-world evidence. Finally, many current IoT initiatives in agriculture are funded by the public sector entities, while the public-private partnership and the long-term sustainability of these initiatives are poorly understood.

These gaps in existing research underline the importance of business models in IoT adoption in agriculture. Innovative business models can bring a wide array of stakeholders together to solve the major barriers in IoT adoption. A promising theoretical avenue in this context might lie in the conditions and mechanisms of value co-creation in IoT business alliances and ecosystems. The three main barriers to IoT adoption in agriculture – cost, lack of skills, and lack of standardization – may be tackled through B2B alliances and networks that enable stakeholders and partners to share the cost and complementary skills, and in doing so, co-create value. Hence, there are interesting theoretical questions surrounding B2B alliances in IoT provision (Sarker *et al.*, 2012), IoT customization versus standardization (Rai and Tang, 2014), the tuning of IoT system boundary resources (Eaton *et al.*, 2015), and organizational capabilities to capture co-created value in the IoT sectors (Schreieck *et al.*, 2021). Addressing IoT adoption barriers in agriculture through these theoretical lenses would help develop business model solutions that build upon a deep understanding of value creation mechanisms in a complex yet highly connected world of IoT stakeholders. Apart from the theoretical insights, this study can also aid industry practitioners to evaluate a range of technical and organizational challenges on the ground.

Finally, it must be noted that this study has some limitations regarding the research design despite the rigor in the selection process and the high number of articles included in the review. It is possible that some relevant publications were missed in the literature search, although the search queries were kept as broad as possible to avoid the exclusion of any relevant work. Any publication written in any other language other than English was excluded from the review. Given the geographical distribution of the reviewed English publications (see section 4.1), it is highly likely that important works written by Chinese and European scholars in their native language were overlooked. Despite the limitations, it is our hope that this literature review lays the groundwork for IS researchers who are well positioned to investigate technology adoption challenges in the relatively understudied agriculture sector.

References

Barenkamp, M. (2020), "A New IoT Gateway for Artificial Intelligence in Agriculture", *2020 International Conference on Electrical, Communication, and Computer Engineering*, pp. 1–5.

Barmpounakis, S., Kaloxylos, A., Groumas, A., Katsikas, L., Sarris, V., Dimtsa, K., Fournier, F., Antoniou, E., Alonistioti, N. and Wolfert, S. (2015), "Management and control applications in Agriculture domain via a Future Internet Business-to-Business platform", *Information Processing in Agriculture*, Vol. 2, No. 1, pp. 51–63.

Bidar, R., Barros, A. and Watson, J. (2022), "Co-creation of services: an online network perspective", *Internet Research*, Vol. 32 No. 3, pp. 897–915.

Brewster, C., Roussaki, I., Kalatzis, N., Doolin, K. and Ellis, K. (2017), "IoT in Agriculture: Designing a Europe-Wide Large-Scale Pilot", *IEEE Communications Magazine*, Vol. 55, No. 9, pp. 26–33.

vom Brocke, J., Simons, A., Niehaves, Bjoern, Niehaves, Bjorn, Reimer, K., Plattfaut, R. and Cleven, A. (2009), "Reconstructing the giant: On the importance of rigour in documenting the literature search process", *Proceedings of the 17th European Conference on Information Systems*, 161.

Chuang, J.-H., Wang, J.-H. and Liang, C. (2020), "Implementation of Internet of Things depends on intention: young farmers' willingness to accept innovative technology", *International Food and Agribusiness Management Review*, Vol. 23, No. 2, pp. 253–265.

Chukkapalli, S. S. L., Mittal, S., Gupta, M., Abdelsalam, M., Joshi, A., Sandhu, R. and Joshi, K. (2020), "Ontologies and Artificial Intelligence Systems for the Cooperative Smart Farming Ecosystem", *IEEE Access*, Vol. 8, pp. 164045–164064.

Eaton, B., Elaluf-Calderwood, S., Sørensen, C. and Yoo, Y. (2015), "Distributed Tuning of Boundary Resources: The Case of Apple's iOS Service System", *MIS Quarterly*, Vol. 39, No. 1, pp. 217–243.

Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y. and Hindia, M. H. D. Nour (2018), "An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges", *IEEE Internet of Things Journal*, Vol. 5, No. 5, pp. 3758–3773.

Fodor, L. (2020), "Precision Agriculture in Hungarian Legal Environment", *Lex ET Scientia International Journal*, Vol. 27 No. 1, pp.41-57.

Goedde, L., Katz, J., Menard, A. and Revellat, J. (2020), "Agriculture's connected future: How technology can yield new growth", *McKinsey & Company*, available at: https://www.mckinsey.com/industries/agriculture/our-insights/agricultures-connected-future-how-technology-can-yield-new-growth (accessed 27 July 2022).

Grammenos, R. and Poole, C. (2019), "Teaching the Internet of Things: The first three years", *2019 26th International Conference on Telecommunications*, Hanoi, Vietnam: IEEE, pp. 265–269.

GSMA Intelligence (2021), "The mobile economy 2021", *GSM Association*, available at: https://www.gsma.com/mobileeconomy/wp-content/uploads/2021/07/GSMA_MobileEconomy2021_3.pdf (accessed 27 July 2022).

Guillen, M. A., Llanes, A., Imbernon, B., Martinez-Espana, R., Bueno-Crespo, A., Cano, J.-C. and Cecilia, J. M. (2021), "Performance evaluation of edge-computing platforms for the prediction of low temperatures in agriculture using deep learning", *Journal of Supercomputing*, Vol. 77, No. 1, pp. 818–840.

Guo, X. (2021), "Application of agricultural IoT technology based on 5G network and FPGA", *Microprocessors and Microsystems*, Vol. 80, p. 103597.

Hadjimanolis, A. (2003), "The Barriers Approach to Innovation", Shavinina, L. V. (Ed.), *The International Handbook on Innovation*, Pergamon, pp. 559–573.

Hang, L., Ullah, I. and Kim, D.-H. (2020), "A secure fish farm platform based on blockchain for agriculture data integrity", *Computers and Electronics in Agriculture*, Vol. 170, p. 105251.

IoT Analytics (2020), "Top 10 IoT applications in 2020", *IoT Analytics*, available at: https://iot-analytics.com/top-10-iot-applications-in-2020/ (accessed 25 July 2022).

Jaisankar, S., Nalini, P. and Rubigha, K. K. (2020), "A Study on IoT based Low-Cost Smart Kit for Coconut Farm Management", *2020 Fourth International Conference on IoT in Social, Mobile, Analytics and Cloud*, pp. 161–165.

Khokhar, T. (2017), "Chart: Globally, 70% of freshwater is used for agriculture", *World Bank Data Blog*, available at: https://blogs.worldbank.org/opendata/chart-globally-70-freshwater-used-agriculture/ (accessed 25 July 2022).

Kitpo, N., Kugai, Y., Inoue, M., Yokemura, T. and Satomura, S. (2019), "Internet of Things for Greenhouse Monitoring System Using Deep Learning and Bot Notification Services", *2019 IEEE International Conference on Consumer Electronics*, pp. 1–4.

Kour, V. P. and Arora, S. (2020), "Recent Developments of the Internet of Things in Agriculture: A Survey", *IEEE Access*, Vol. 8, pp. 129924–129957.

Kuaban, G. S., Czekalski, P., Molua, E. L. and Grochla, K. (2019), "An Architectural Framework Proposal for IoT Driven Agriculture", Gaj, P., Sawicki, M. & Kwiecien, A. (Ed.s), *Computer Networks. 26th International Conference,* Vol. 1039, pp. 18–33.

Lezoche, M., Hernandez, J. E., Díaz, M. del M. E. A., Panetto, H. and Kacprzyk, J. (2020), "Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture", *Computers in Industry*, Vol. 117, p. 103187.

Li, S., Tryfonas, T. and Li, H. (2016), "The Internet of Things: a security point of view", *Internet Research*, Vol. 26 No. 2, pp. 337–359.

Lopez-Viana, R., Diaz, J., Hernandez Diaz, V. and Martinez, J.-F. (2020), "Continuous Delivery of Customized SaaS Edge Applications in Highly Distributed IoT Systems", *IEEE Internet of Things Journal*, Vol. 7, No. 10, pp. 10189–10199.

Luo, H., Zhu, M., Ye, S., Hou, H., Chen, Y. and Bulysheva, L. (2016), "An intelligent tracking system based on internet of things for the cold chain", *Internet Research*, Vol. 26, No. 2, pp. 435–445.

Ma, N., Pan, L., Chen, S. and Liu, B. (2020), "NB-IoT Estrus Detection System of Dairy Cows Based on LSTM Networks", *2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 1–5.

Mondragon, A. E. C., Mondragon, C. E. C. and Coronado, E. S. (2020), "Managing the food supply chain in the age of digitalisation: a conceptual approach in the fisheries sector", *Production Planning & Control*, Vol.32, No.3, pp. 1–14.

Navarro, E., Costa, N. and Pereira, A. (2020), "A Systematic Review of IoT Solutions for Smart Farming", *Sensors*, Vol. 20, No. 15, p. 4231.

Nesarani, A., Ramar, R. and Pandian, S. (2020), "An efficient approach for rice prediction from authenticated Block chain node using machine learning technique", *Environmental Technology & Innovation*, Vol. 20, p. 101064.

Nigussie, E., Olwal, T., Musumba, G., Tegegne, T., Lemma, A. and Mekuria, F. (2020), "IoT-based Irrigation Management for Smallholder Farmers in Rural Sub-Saharan Africa", *Procedia Computer Science*, Vol. 177, pp. 86–93.

O'Grady, M. J. and O'Hare, G. M. P. (2017), "Modelling the smart farm", *Information Processing in Agriculture*, Vol. 4, No. 3, pp. 179–187.

Padyab, A., Habibipour, A., Rizk, A. and Stahlbroest, A. (2020), "Adoption Barriers of IoT in Large Scale Pilots", *Information*, Vol. 11, No. 1, p. 23.

Pasquale, G. D., Graziani, S., Pollicino, A. and Trigona, C. (2019), ""Paper" Based Sensor for Deformation Measurements", *2019 IEEE International Instrumentation and Measurement Technology Conference*, pp. 1–5.

Pham, C., Rahim, A. and Cousin, P. (2016), "Low-cost, Long-range Open IoT for Smarter Rural African Villages", *2016 IEEE Second International Smart Cities Conference*, pp. 1–6.

Pillai, R. and Sivathanu, B. (2020), "Adoption of internet of things (IoT) in the agriculture industry deploying the BRT framework", *Benchmarking: An International Journal*, Vol. 27, No. 4, pp. 1341–1368.

Pivoto, D., Waquil, P. D., Talamini, E., Finocchio, C. P. S., Dalla Corte, V. F. and de Vargas Mores, G. (2018), "Scientific development of smart farming technologies and their application in Brazil", *Information Processing in Agriculture*, Vol. 5, No. 1, pp. 21–32.

Rai, A. and Tang, X. (2014), "Research Commentary — Information Technology-Enabled Business Models: A Conceptual Framework and a Coevolution Perspective for Future Research", *Information Systems Research*, Vol. 25, No. 1, pp. 1–14.

Rao, P. B. B., Saluja, P., Sharma, N., Mittal, A. and Sharma, S. V. (2012), "Cloud Computing for Internet of Things & Sensing Based Applications", *2012 Sixth International Conference on Sensing Technology*, pp. 374–380.

Rodriguez-Robles, J., Martin, A., Martin, S., Ruiperez-Valiente, J. A. and Castro, M. (2020), "Autonomous Sensor Network for Rural Agriculture Environments, Low Cost, and Energy Self-Charge", *Sustainability*, Vol. 12, No.15, p. 5913.

Ronaghi, M. H. and Forouharfar, A. (2020), "A contextualized study of the usage of the Internet of things (IoTs) in smart farming in a typical Middle Eastern country within the context of Unified Theory of Acceptance and Use of Technology model (UTAUT)", *Technology in Society*, Vol. 63, p. 101415.

Roussaki, I., Kosmides, P., Routis, G., Doolin, K., Pevtschin, V. and Marguglio, A. (2019), "A Multi-Actor Approach to promote the employment of IoT in Agriculture", *2019 Global IoT Summit*, pp. 1–6.

Ruan, J., Wang, Y., Chan, F. T. S., Hu, X., Zhao, M., Zhu, F., Shi, B., Shi, Y. and Lin, F. (2019), "A Life Cycle Framework of Green IoT-Based Agriculture and Its Finance, Operation, and Management Issues", *IEEE Communications Magazine*, Vol. 57, No. 3, pp. 90–96.

Salam, A., Vuran, M. C. and Irmak, S. (2019), "Di-Sense: In situ real-time permittivity estimation and soil moisture sensing using wireless underground communications", *Computer Networks*, Vol. 151, pp. 31–41.

Sales, F. O., Marante, Y., Vieira, A. B. and Silva, E. F. (2020), "Energy Consumption Evaluation of a Routing Protocol for Low-Power and Lossy Networks in Mesh Scenarios for Precision Agriculture", *Sensors*, Vol. 20, No. 14, p. 3814.

Sarker, S., Sarker, S., Sahaym, A. and Bjørn-Andersen, N. (2012), "Exploring Value Cocreation in Relationships Between an ERP Vendor and its Partners: A Revelatory Case Study", *MIS Quarterly*, Vol. 36, No. 1, p. 317.

Schreieck, M., Wiesche, M. and Krcmar, H. (2021), "Capabilities for value co-creation and value capture in emergent platform ecosystems: A longitudinal case study of SAP's cloud platform", *Journal of Information Technology*, Vol. 36, No. 4, pp. 365–390.

Sharma, A., Jain, A., Gupta, P. and Chowdary, V. (2021), "Machine Learning Applications for Precision Agriculture: A Comprehensive Review", *IEEE Access*, Vol. 9, pp. 4843–4873.

Shi, X., An, X., Zhao, Q., Liu, H., Xia, L., Sun, X. and Guo, Y. (2019), "State-of-the-Art Internet of Things in Protected Agriculture", *Sensors*, Vol. 19, No. 8, p. 1833.

Takagi, C., Purnomo, S. H. and Kim, M.-K. (2021), "Adopting Smart Agriculture among organic farmers in Taiwan", *Asian Journal of Technology Innovation*, Vol. 29, No. 2, pp. 180–195.

Tang, Y., Dananjayan, S., Hou, C., Guo, Q., Luo, S. and He, Y. (2021), "A survey on the 5G network and its impact on agriculture: Challenges and opportunities", *Computers and Electronics in Agriculture*, Vol. 180, p. 105895.

Toriyama, K. (2020), "Development of precision agriculture and ICT application thereof to manage spatial variability of crop growth", *Soil Science and Plant Nutrition*, Vol. 66, No.8, pp. 811–819.

Trilles, S., Gonzalez-Perez, A. and Huerta, J. (2020), "An IoT Platform Based on Microservices and Serverless Paradigms for Smart Farming Purposes", *Sensors*, Vol. 20, No. 8, p. 2418.

Trinoskey, J., Brahmi, F. A. and Gall, C. (2009), "Zotero: A Product Review", *Journal of Electronic Resources in Medical Libraries*, Vol. 6, No. 3, pp. 224–229.

Tzounis, A., Katsoulas, N., Bartzanas, T. and Kittas, C. (2017), "Internet of Things in agriculture, recent advances and future challenges", *Biosystems Engineering*, Vol. 164, pp. 31–48.

Valecce, G., Petruzzi, P., Strazzella, S. and Grieco, L. A. (2020), "NB-IoT for Smart Agriculture: Experiments from the Field", *2020 7th International Conference on Control, Decision and Information Technologies*, Vol.1, pp. 71–75.

Varandas, L., Faria, J., Gaspar, P. D. and Aguiar, M. L. (2020), "Low-Cost IoT Remote Sensor Mesh for Large-Scale Orchard Monitorization", *Journal of Sensor and Actuator Networks*, Vol. 9, No. 3, p. 44.

Verdouw, C., Sundmaeker, H., Tekinerdogan, B., Conzon, D. and Montanaro, T. (2019), "Architecture framework of IoT-based food and farm systems: A multiple case study", *Computers and Electronics in Agriculture*, Vol. 165, p. 104939.

Villa-Henriksen, A., Edwards, G. T. C., Pesonen, L. A., Green, O. and Sørensen, C. A. G. (2020), "Internet of Things in arable farming: Implementation, applications, challenges and potential", *Biosystems Engineering*, Vol. 191, pp. 60–84.

Vincent, D. R., Deepa, N., Elavarasan, D., Srinivasan, K., Chauhdary, S. H. and Iwendi, C. (2019), "Sensors Driven AI-Based Agriculture Recommendation Model for Assessing Land Suitability", *Sensors*, Vol. 19, No. 17, p. 3667.

Wang, N., Liang, H., Ge, S., Xue, Y. and Ma, J. (2019), "Enablers and inhibitors of cloud computing assimilation: an empirical study", *Internet Research*, Vol. 29, No. 6, pp. 1344–1369.

Wang, Q. and Yang, X. (2014), "Research on IOT Based Special Supply Mode of Agricultural Products", Chang, L., Guiran, C. & Zhen, L. (Ed.s), *Proceedings of the 2014 International Conference on Mechatronics, Electronic, Industrial and Control Engineering*, pp. 1740–1743.

Webster, J. and Watson, R. T. (2002), "Analyzing the Past to Prepare for the Future: Writing a Literature Review", *MIS Quarterly*, Vol. 26, No. 2, pp. xiii–xxiii.

World Bank (2021), "Agriculture, forestry, and fishing, value added (% of GDP)", available at: https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS (accessed 27 July 2022).

Wu, F. and Ma, J. (2020), "Evolution Dynamics of Agricultural Internet of Things Technology Promotion and Adoption in China", *Discrete Dynamics in Nature and Society*, Vol. 2020, pp. 1–18.

Xiang, F. and Wang, D. (2020), "Research on Operation Mode of "internet plus" Agricultural Products Intelligent Supply Chain", *2020 International Conference on Urban Engineering and Management Science*, pp. 208–211.

Yang, C.-Y., Yang, M.-D., Tseng, W.-C., Hsu, Y.-C., Li, G.-S., Lai, M.-H., Wu, D.-H. and Lu, H.-Y. (2020), "Assessment of Rice Developmental Stage Using Time Series UAV Imagery for Variable Irrigation Management", *Sensors*, Vol. 20, No. 18, p. 5354.

Yang, X., Shu, L., Chen, J., Ferrag, M. A., Wu, J., Nurellari, E. and Huang, K. (2021), "A Survey on Smart Agriculture: Development Modes, Technologies, and Security and Privacy Challenges", *IEEE/CAA Journal of Automatica Sinica*, Vol. 8, No. 2, pp. 273–302.

Yu, X.-Y. and Guo, X.-H. (2020), "Data anomaly detection and Data fusion based on Incremental Principal Component Analysis in Fog Computing", *KSII Transactions on Internet and Information Systems*, Vol. 14, No. 10, pp. 3989–4006.

Zhang, M.-Z., Wang, L.-M. and Xiong, S.-M. (2020), "Using Machine Learning Methods to Provision Virtual Sensors in Sensor-Cloud", *Sensors*, Vol. 20, No. 7, p. 1836.

Zhu, J. and Sun, N. (2012), "Research on Integration of WSN and RFID Technology for Agricultural Product Inspection", *2012 International Conference on Industrial Control and Electronics Engineering*, pp. 908–911.