IoT adoption in agriculture: a systematic review

Completed Research

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Abstract

Agriculture is one of these sectors where Internet of Things (IoT) is expected to make a major impact. Yet, its adoption in the sector falls behind the expectations. This paper presents an extensive review of 1355 publications over the last decade, with an aim to highlight the state-of-the-art of research on IoT in agriculture and investigate its slow adoption. The literature review reveals that the "big three" barriers for the overall sector are cost, skills, and standardization, while the lack of connectivity and data governance are two key reasons why most of the proposed IoT solutions are standalone systems of limited scope and the majority of commercial IoT efforts focuses on practices under protected indoor environment. Lastly, the analysis of past research along the five layers of IoT system architecture reveals limited attention on barriers and solutions at the business layer, which represents a research opportunity for information systems scholars.

Keywords

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

Introduction

With an estimated 13.1 billion connected devices today (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 of 2020 as compared to manufacturing with 22% (IoT Analytics 2020). Yet, agriculture is one of the sectors where 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 7-9%, using IoT would translate to $500 billion in contribution to the global GDP within next ten years as predicted by Goedde et al. (2020). Economic benefits aside, application of IoT technology in agriculture also would have a positive impact on environment and human health by reducing 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 public and industry, IoT in agriculture has caught a great attention in the academia with an exponential number of publications since 2015. 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) and connectivity (Pham et al. 2016), yet in reality vast majority of IoT ventures in agriculture 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. While there is a growing body of literature that recognizes the lack of IoT adoption in agriculture and its related factors, our understanding of it remains incomplete as most studies only provide a generic overview with limited in-depth investigation. There have been few studies with substantial coverage of adoption barriers. For example, Pillai and Sivathanu (2020) attempted to identify the adoption barriers in the Indian context surveying 2,885 farmers, while Pivoto et al. (2018) run semi-structured interviews with industry experts – not the farmers – to understand main barriers to the IoT adoption in Brazilian agriculture. Despite providing significant insights, the findings of these studies are bounded by the circumstances within which or for which the research was conducted, and therefore have a limited generalizability.

In light of this research gap, we seek to undertake an extensive review and a synthesis of relevant publications from 2010 to date, with an aim to present the state-of-the-art of IoT in agriculture and investigate its slow adoption in the sector. To start with, we need to know about the challenges highlighted by the existing research for lack of IoT adoption in agriculture. This will help the audience to understand specific challenges associated with technology, region, and type (e.g., indoor versus outdoor) of agriculture. Hence, the first research question this paper aims to address is:

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

Next, we examine how the existing research managed to address the barriers identified in the literature. This will help to uncover gaps and shortcomings in research so as to provide a direction for further research. Therefore, our second research question is:

RQ2 – How has the IoT research in agriculture addressed the adoption barriers?

In the remainder of the paper, the scope of the research and the methodology will be presented. Next, the main findings of the research will be presented and discussed. Finally, the paper concludes and provides recommendations for further research.

Research scope and methodology

This study reviews academic work on IoT in agriculture published in the last decade between 2010 and early 2021, following an approach adapted from Brocke et al. (2009) for search and screening. Although the literature on IoT is found predominantly within the information systems (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, academic publications were retrieved to cover all relevant terms such as “smart agriculture”, “precision agriculture”, “agricultural”, “agri-iot”, or terms that are used interchangeably such as “farming”, “farmland” etc.

Sample Query	("internet of things" OR "iot") AND ("agri*" OR "farm*")			
Filtered by	Year:	2010 - 2021		
	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

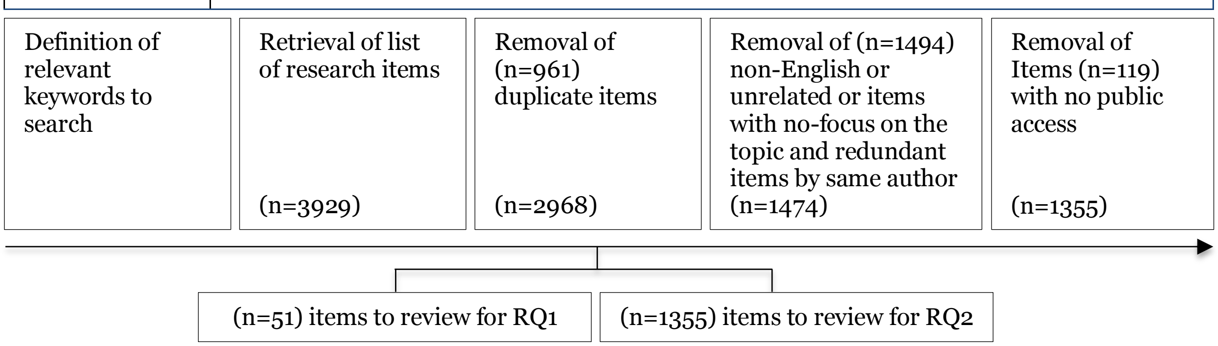

Figure 1: Search scope and screening process

As illustrated in Figure 1, the initial search running the query, e.g., ("internet of things" OR "iot") AND ("agri*" OR "farm*") on eight widely used online databases returned 3929 research items including peerreviewed published articles, conference papers and book chapters, which have been found to contain relevant keywords in their abstract section. As the next step, the duplicate items have been 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, have been identified and removed. Also, the redundant items published by the same author(s) in a different format (journal/conference) have been 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 both research questions.

Regarding the analysis of barriers (RQ1), 51 items were 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 2 depicts our overall framework for the literature analysis.

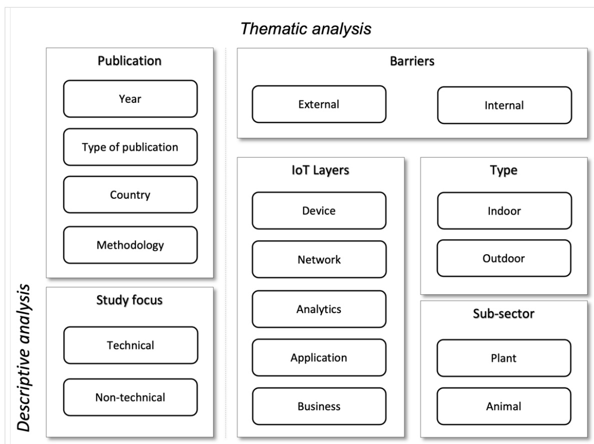

Figure 2: Conceptual framework for literature analysis

Descriptive analysis

The analysis of the publication years of 1355 studies from 2010 to early 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, 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. Each year since then there has been 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 of researchers in IoT for agriculture.

More than half of analyzed publications 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 (91%, 1280 items), while the number of non-technical studies (9%, 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. In terms of research methodology, the majority of analyzed studies adopted a quantitative approach. Experiment (42%, 575 items) came out as the most popular methodology employed mainly by studies with technical focus to test the applicability of 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 (14%, 182 items) and simulation (8%, 108 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%, 36 items) and survey (0.7%, 10 items). The analysis reveals a significant scarcity of empirical research found within non-technical studies, where only 3% (38 items) of all publications provides empirical evidence.

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. Taken together, the distribution of publications by geography and year reveals that most of early studies until 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 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 projects backed by the EU's Horizon 2020 initiative (e.g., Roussaki et al. 2019).

Thematic analysis

Barriers to IoT adoption in agriculture (RQ1)

Barriers to adoption of IoT in agriculture are numerous and diverse. For a better overview and understanding of the identified barriers, a taxonomy adopted from Hadjimanolis (2003) is used to categorize the results from the analysis of 51 selected publications. Figure 3 provides a summary of seven main barrier categories which broadly are classified as external and internal, and further divided into themes and ranked according to the frequency of appearance in the coding. 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.

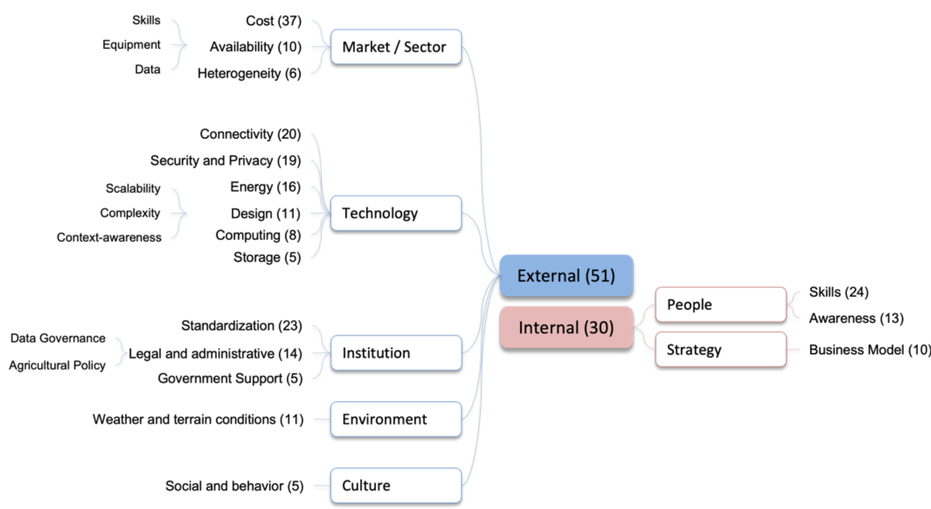

Figure 3: Taxonomy of barriers to IoT adoption

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 external barriers clearly outweighs that of the internal barriers in terms of number of factors hampering the IoT adoption in agriculture.

Among the market related barriers, cost (73%, 37 items) has been cited as the leading factor with an impact across multiple IoT layers including the device layer, e.g., 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). In the context of high-income economies, on the other hand, it shows that the cost is equally a concerning factor for the wealthy farmers, e.g. in United States (Chukkapalli et al. 2020), but the reason being lack of return of investment (ROI).

Limited availability (20%, 10 items) of hardware equipment, technical expertise and data is another market related barrier with an impact felt across all IoT layers, and types and sub-sectors of agriculture. IoT equipment such as sensors are not available to buy at all (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 in developing countries to implement and support the IoT solution on the ground (Kuaban et al. 2019). Other studies report lack of availability of open data (e.g., Xiang and Wang 2020) in the sector. The heterogeneous nature of agriculture (12%, 6 items) is also a 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.

Technical barriers make up the second largest group of publications, led by connectivity (40%, 20 items). This is a rather 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 still highlight the lack of reliable connectivity as the primary factor for slow diffusion of IoT technology in the context of rural agriculture (Lezoche et al. 2020). Security and privacy (37%, 19 items) are two major technical barriers that are often found associated with each other. In addition to vulnerability of sensors and network equipment to physical attacks (Tzounis et al. 2017), past research had identified the threat to integrity and confidentiality of data (Yang et al. 2021) as data circulate across multiple IoT layers. Our analysis shows no difference in perception of security and privacy threats among the farmers in respect to the region and sub-sector of agriculture. Compared to indoor agriculture (e.g., green- or glasshouse), however, 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). Energy (31%, 16 items) has been named as a significant barrier 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).

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 impact multiple layers. Scalability barrier may manifest at 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). 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). 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 surroundings (Villa-Henriksen et al. 2020). Although to the lesser extent, lack of computing power (16%, 8 items) and lack of storage (10%, 5 items) 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).

Institutional barriers are extensively covered in the literature, led by the discussion on standardization (45%, 23 items), which came out as the third most cited barrier overall in the analysis. While early studies (e.g., Qingjun and Xiaoxue 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 to the emergence of too many standards as a barrier underlining the need for institutional leadership to create global open standards (Shi et al. 2019). Most studies covering legal and administrative barriers (27%, 14 items) highlight the lack of data governance as a barrier to IoT adoption in the sector. 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 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 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. 2020).

Despite being covered by a relatively small number of publications, environment (22%, 11 items) and culture (10%, 5 items) can also pose challenges to IoT adoption in agriculture. Difficult environment and terrain conditions can be detrimental as the IoT equipment are exposed to the extreme weather conditions that can lead to sensor and communication failures (Villa-Henriksen et al. 2020). Culture barriers are highly context-based societal and behavioral factors (Lezoche et al. 2020) that result in, for example, the resistance to change due to work habits (Brewster et al. 2017).

With regard to people related barriers, two challenges 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. 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 availability and potential benefits of IoT technology in the first place (Wu and Ma 2020). Relatedly, 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 not sustainable.

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

Having identified the barriers to the adoption of IoT in agriculture, this section of the paper attempts to answer the question: how has the IoT research in agriculture addressed the adoption barriers? For clarity, we organize the literature analysis according to the five IoT layers shown in Figure 2.

The device layer (70%, 955 items) consists of "things" that capture data from 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 to an stronger role of unmanned aerial vehicles (UAVs) and robotics in the outdoor agriculture for crop production activities such as detection of water stress (e.g., Yang et al., 2020). The key advantage of UAVs and robotic devices over static sensor networks is the mobility, which would lead to significant cost savings by removing the need for deployment of multiple sensors to cover a large area to monitor.

The network layer (78%, 1060 items), which 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., Zhao et al. 2010) consisting of three-layered architecture using wired and short-range wireless 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, Jiang et al. (2021) proposed and tested a solution using a hybrid network including LoRa, a low-power wide-area wireless technology to address the barriers related to reliable rural connectivity, harsh environment, cost, and energy consumption. 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. Several recent studies investigate novel network architectures such as edge or fog computing that may mitigate impact of barriers related to connectivity, environment, energy, and scalability by reducing the network load through local storage and data processing at the edge level (Guillen et al. 2021). There are also opportunities for better connectivity and energy savings through 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.

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 modelling with high volume of data. Coupled with analytics and machine learning, cloud-based IoT solutions are capable of covering full cycle of crop production from assessing land suitability for cultivation (e.g., Vincent et al., 2019) 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 storage and processing of data to the edge or device level, 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.

The application layer (66%, 891 items) is the user interaction layer of an IoT system consisting of front- and back-end applications. The emergence of new approaches to the modular system design such as use of microservices and containers (Trilles et al. 2020) have 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 the scope and function. One trend worth highlighting in the application layer is the emergence of Augmented and Mixed Reality (AR and MR) technologies, which takes the user interactivity to the next level by introducing the idea of digital twin (Dietz and Pernul 2020) to agriculture for mirroring physical objects (X. Zhang 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).

The business layer (7%, 90 items) is the layer of management of an IoT system that involves modelling and integrating existing business processes around a business model with 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 modelling 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 (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 maintenance of software at the network layer (e.g., Lopez-Viana et al., 2020), platform as a service (PaaS) model for cloud-based infrastructure provisioning at the analytics and application layers (e.g., Barmpounakis et al., 2015) and sensors as a service (Se-aaS) model for sensor provisioning at the 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. In terms of co-operation, FIspace is a good example of co-operation initiatives 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). Regarding co-creation, Demeter, another initiative by the EU is to highlight, which introduces a multi-actor approach to the system design for supporting an inclusive value chain mechanism between farmers and suppliers (Roussaki et al. 2019). In respect to co-ownership, Chukkapalli et al. (2020) propose value propositions based on integrating IoT into existing traditional co-op ecosystem for a collective ownership of cost and benefits of an IoT system.

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. 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 number of published studies, the findings 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 weight of external barriers is apparent, there is no single barrier alone responsible for the slow adoption. 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-subsectors 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 (Chong et al. 2019). The majority of proposed IoT solutions to date are standalone systems with limited scope and function with irrigation is being the leading application area.

Our analysis by IoT layer indicates that the network and analytics layers get most attention and research contribution. This is mainly due to emerging technologies such as cloud computing and low-power wide-area wireless technologies, which help to address some of the identified barriers in connectivity, energy, storage, among others. Somewhat surprisingly, our analysis shows that lack of connectivity is still a leading technical barrier to IoT implementation and adoption, not only in developing countries with limited infrastructure but worldwide. Consequently, the connectivity barrier becomes the primary reason why the rural outdoor agriculture today is lagging behind in terms of adopting and benefiting from IoT.

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, which is unlikely to be sustainable in the long run. These gaps in the existing research underline the importance of business models, as innovative business models can bring a wide array of stakeholders together to solve the major barriers in IoT adoption. It is our hope that this literature review lays the groundwork for information systems researchers who are well positioned to investigate technology innovations such as IoT from a business angle - to make novel contributions to the field.

REFERENCES

Barenkamp, M. 2020. "A New IoT Gateway for Artificial Intelligence in Agriculture," in *2020 International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*, June 12, 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* (2:1), pp. 51–63.

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* (55:9), pp. 26–33.

Brocke, J. vom, 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*.

Chong, A. Y. L., Lim, E. T. K., Hua, X., Zheng, S., and Tan, C.-W. 2019. "Business on Chain: A Comparative Case Study of Five Blockchain-Inspired Business Models," *Journal of the Association for Information Systems* (20:9).

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* (8), pp. 164045–164064.

Dietz, M., and Pernul, G. 2020. "Digital Twin: Empowering Enterprises Towards a System-of-Systems Approach," *Business & Information Systems Engineering* (Vol. 62), pp. 179–184.

Goedde, L., Katz, J., Menard, A., and Revellat, J. 2020. “Agriculture’s Connected Future: How Technology Can Yield New Growth,” *New York, NY: McKinsey & Company*.

GSMA Intelligence. 2021. “The Mobile Economy 2021,” *London: GSM Association*.

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* (77:1), pp. 818–840.

Guo, X. 2021. “Application of Agricultural IoT Technology Based on 5G Network and FPGA,” *Microprocessors and Microsystems* (80), p. 103597.

Hadjimanolis, A. 2003. “The Barriers Approach to Innovation,” in *The International Handbook on Innovation*, L. V. Shavinina (ed.), Oxford: Pergamon, pp. 559–573.

IoT Analytics. 2020. “Top 10 IoT Applications in 2020,” *IoT Analytics*.

Jaisankar, S., Nalini, P., and Rubigha, K. K. 2020. “A Study on IoT Based Low-Cost Smart Kit for Coconut Farm Management,” in *2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, October 7, pp. 161–165.

Jiang, X., Zhang, H., Yi, E. A. B., Raghunathan, N., Mousoulis, C., S. Chaterji, D. Peroulis, A. Shakouri, and S. Bagchi. 2021. “Hybrid Low-Power Wide-Area Mesh Network for IoT Applications,” *IEEE Internet of Things Journal* (8:2), pp. 901–915.

Khokhar, T. 2017. “Chart: Globally, 70% of Freshwater Is Used for Agriculture,” *World Bank Data Blog*.

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

Kuaban, G. S., Czekalski, P., Molua, E. L., and Grochla, K. 2019. “An Architectural Framework Proposal for IoT Driven Agriculture,” in *Computer Networks, Cn 2019* (Vol. 1039), P. Gaj, M. Sawicki, and A. Kwiecien (eds.), 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* (117), p. 103187.

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* (7:10), pp. 10189–10199.

Navarro, E., Costa, N., and Pereira, A. 2020. “A Systematic Review of IoT Solutions for Smart Farming,” *Sensors* (20:15), p. 4231.

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* (177), pp. 86–93.

Pasquale, G. D., Graziani, S., Pollicino, A., and Trigona, C. 2019. “‘Paper’Based Sensor for Deformation Measurements,” in *2019 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, May 20, pp. 1–5.

Pham, C., Rahim, A., and Cousin, P. 2016. “Low-Cost, Long-Range Open IoT for Smarter Rural African Villages,” *Ieee Second International Smart Cities Conference (Isc2 2016)*, pp. 512–517.

Pillai, R., and Sivathanu, B. 2020. “Adoption of Internet of Things (IoT) in the Agriculture Industry Deploying the BRT Framework,” *Benchmarking: An International Journal* (27:4), Emerald Publishing Limited, 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* (5:1), pp. 21–32.

Qingjun, W., and Xiaoxue, Y. 2014. “Research on IOT Based Special Supply Mode of Agricultural Products,” in *Proceedings of the 2014 International Conference on Mechatronics, Electronic, Industrial and Control Engineering* (Vol. 5), L. Chang, C. Guiran, and L. Zhen (eds.), pp. 1715–1718.

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

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,” in *2019 Global IoT Summit (GIoTS)*, June 17, 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* (57:3), 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* (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* (20:14), p. 3814.

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* (19:8), p. 1833.

Takagi, C., Purnomo, S. H., and Kim, M.-K. 2020. "Adopting Smart Agriculture among Organic Farmers in Taiwan," *Asian Journal of Technology Innovation*, Routledge, pp. 1–16.

Toriyama, K. 2020. "Development of Precision Agriculture and ICT Application Thereof to Manage Spatial Variability of Crop Growth," *Soil Science and Plant Nutrition*, Taylor & Francis, pp. 1–9.

Trilles, S., González-Pérez, A., and Huerta, J. 2020. "An IoT Platform Based on Microservices and Serverless Paradigms for Smart Farming Purposes," *Sensors* (20:8), Basel: MDPI AG, p. 2418.

Tzounis, A., Katsoulas, N., Bartzanas, T., and Kittas, C. 2017. "Internet of Things in Agriculture, Recent Advances and Future Challenges," *Biosystems Engineering* (164), pp. 31–48.

Valecce, G., Petruzzi, P., Strazzella, S., and Grieco, L. A. 2020. "NB-IoT for Smart Agriculture: Experiments from the Field," in *2020 7th International Conference on Control, Decision and Information Technologies (CoDIT)* (Vol. 1), July 29, 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* (9:3), 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* (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* (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* (19:17), p. 3667.

Webster, J., and Watson, R. T. 2002. "Analyzing the Past to Prepare for the Future: Writing a Literature Review," *MIS Quarterly* (26:2), Management Information Systems Research Center, University of Minnesota, pp. xiii–xxiii.

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* (2020), (Youssef N Raffoul, ed.), New York: Hindawi Limited.

Xiang, F., and Wang, D. 2020. "Research on Operation Mode of 'Internet plus' Agricultural Products Intelligent Supply Chain," in *2020 International Conference on Urban Engineering and Management Science (ICUEMS)*, , April 24, 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* (20:18), 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* (8:2), pp. 273–302.

Zhang, M.-Z., Wang, L.-M., and Xiong, S.-M. 2020. "Using Machine Learning Methods to Provision Virtual Sensors in Sensor-Cloud," *Sensors* (20:7), p. 1836.

Zhang, X., Cao, Z., and Dong, W. 2020. "Overview of Edge Computing in the Agricultural Internet of Things: Key Technologies, Applications, Challenges," *Ieee Access* (8), pp. 141748–141761.

Zhao, J., Zhang, J., Feng, Y., and Guo, J. 2010. "The Study and Application of the IOT Technology in Agriculture," in *Iccsit 2010 - 3rd Ieee International Conference on Computer Science and Information Technology, Vol 2*, Y. Hang, W. Desheng, and P. S. Sandhu (eds.), pp. 462–465.