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Using AI to Improve Sustainable Agricultural Practices: A Literature Review and Research Agenda

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Using AI to Improve Sustainable Agricultural Practices: A Literature Review and Research Agenda

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Abstract:

The world is confronted with the grand challenge of food insecurity amidst growing populations and the climate crisis. Artificial intelligence (AI) deployed in agricultural decision support systems (AgriDSS) raises both hopes and concerns for increasing agricultural productivity in sustainable ways. In this paper, we conduct a scoping review to uncover the roadblocks to the use of AI-supported AgriDSS in sustainable agriculture. Based on the corpus of 121 articles, we find that the effective use of AI-supported AgriDSS is hindered at technical, social, ethical, and ecological levels. Then, drawing on the experiential learning perspective, we propose how conjoint experiential learning (CEL) can enhance sustainable agricultural practices by enhancing both AI and human learning and overcoming roadblocks in using AgriDSS. Based on this conceptual framework, we build a research agenda that suggests blind spots and possible directions for future research.

Keywords: Agriculture, Artificial Intelligence, AgriDss, Sustainability, AI Capabilities, Experiential Learning.

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1 Introduction

The agricultural sector, an industry worth five trillion US dollars worldwide, is turning to sophisticated technologies like artificial intelligence (AI) to transform conventional agriculture into sustainable agriculture (Bestelmeyer et al., 2022; Modgil et al., 2020). These technology initiatives respond to the need to tackle the global challenge of food security by promoting agricultural practices that increase crop productivity while having minimal impact on the environment (Marr, 2020; Spanaki et al., 2022a). The pursuit of agricultural sustainability and global food security, the dual aim of the United Nation's second sustainable development goal (SDG-2), requires the agricultural sector to manage the complexity of a wider range of agro-ecological and socio-technological processes (Galaz et al., 2021; UN, 2015). AI as a technology does not work independently but rather supplements existing information systems (IS) applications known as agricultural decision support systems (AgriDSS) to boost sustainable agricultural practices (Liakos et al., 2018). AI-supported AgriDSS tackle complex agricultural problems by integrating data and providing real-time predictive insights (Bochtis et al., 2012; Modgil et al., 2020). As the next generation of farming technologies, AI-supported AgriDSS will shape the evolution of agrarian operations (Spanaki et al., 2022b) and contribute to achieving long-term sustainability goals (Lindblom et al., 2017).

Despite their increasing popularity, AI-supported AgriDSS deployed to date remain underutilized (Lindblom et al., 2017). The design of these systems is influenced by designers' perceptions and algorithmic models trained on historical data (Abbasi et al., 2022; Choudhury et al., 2020). The absence of context-awareness and the reliance on historical data can make AI-supported AgriDSS models susceptible to prediction biases and recommendation ambiguities under environmental uncertainties (Abbasi et al., 2022). The inability of AI systems to coalesce decision-making with uncertainty management is an important gap in the effective implementation and use of AgriDSS in agriculture and necessitates more research (Abioye et al., 2022).

IS researchers have been called to solve grand societal challenges (Gholami et al., 2016). Although agricultural technology has not been a main area of interest for IS researchers over the last 50 years, the IS discipline now has an opportunity, and a responsibility, to be involved in the agricultural sector as sustainable crop production and environmental sustainability are pressing societal needs (Kurkalova & Carter, 2017; Qureshi et al., 2021). Examining AI in sustainable agriculture can be a potentially rich and important research stream in green IS (Nishant et al., 2020), with implications for using and developing AI in other environmental and social contexts. While recognizing that well-developed knowledge around the design and use of IS undoubtedly has relevance to questions related to AI and other agricultural technologies (García Pereira et al., 2020; Ginige et al., 2020; Newlands et al., 2019; Ofori & El-Gayar, 2020), we argue that the distinctive nature of AI necessitates new perspectives. Literature on the interaction between humans and AI (Tarafdar et al., 2022) suggests a continuous transformation of human knowledge (Grønsund & Aanestad, 2020; Raisch & Krakowski, 2021). This continuous knowledge transformation and evolution complicates examining the nature and type of collaboration between users and AI systems. Consequently, examining this phenomenon requires an in-depth comprehension of the context. Hence, we propose experiential learning as a possible lens to examine the AI phenomenon.

Experiential learning is a process that generates knowledge through the transformation of experiences (Kolb, 1984). Traditionally, individual farmers relied on experiential learning to make crop planting and harvesting decisions, but with the rise of AgriDSS use, farmers and other agricultural workers have become more reliant on technologies for decision-making (Lindblom et al., 2017). The designs of these artifacts often do not consider the dynamism of the agricultural settings, leading to decision errors and ineffective use (Van Meensel et al., 2012). Farmers' field experiences allow them to solve critical farming problems by providing insights into the phenomenon occurring within the dynamic agricultural environment. An experiential learning approach focuses on individuals' experiences and guides the cognitive processes that use these experiences to make future decisions (Mao et al., 2020; Lindblom et al., 2017). Examining the interaction between technology and agricultural contexts through farmers' experiential learning perspective could lead to a more effective design and use of AgriDSS, resulting in better sustainable outcomes. Thus, the main question guiding this research is:

> **MRQ: How roadblocks to AgriDSS use can be addressed to enhance its performance for sustainable agriculture?**

As a starting point for answering this question, we review the literature on the use of AI-supported AgriDSS for sustainable agriculture. We specifically focus on AI-supported AgriDSS and, for clarity, use the term AgriDSS to represent this specific class of technology. A literature review offers an appropriate method for conceptualizing a research topic, identifying research gaps, and developing a research agenda (Schryen et al., 2020). Based on the review's findings and our theorizing, we then develop a conceptual framework for conjoint learning that outlines how human experiential learning and AI data-driven learning can be combined to enhance AI capabilities and support the development and use of robust AgriDSS for sustainable agriculture. Based on this framework, we propose a research agenda and opportunities for future IS research.

The rest of the paper is structured as follows. Section 2 discusses relevant research on AgriDSS for sustainable agriculture. Sections 3 and 4 present the research methodology and findings of the scoping review. Section 5 develops the conceptual framework, and section 6 presents the research agenda. The paper concludes with limitations and contributions, as discussed in section 7.

2 Background

2.1 AgriDSS in Sustainable Agriculture

Technological developments have provided diverse business sectors with immense opportunities to improve competitiveness and business performance. Technological advancements, like AI, big data, and the Internet of Things (IoT), have disrupted conventional business and revolutionized business models (Bannerjee et al., 2018). Among these technologies, AI has gained attention from academia and the business world due to its expected benefits in several sectors, such as education, business, finance, and agriculture (Bannerjee et al., 2018). In combination with other technologies like IoT, big data, and analytics, AI can significantly improve the efficiency of AgriDSS (Van Meensel et al., 2012). For instance, combined with real-time AI applications, big data can provide farmers with predictive insights and detailed recommendations to support farmers' operational and strategic decision-making (Liakos et al., 2018).

The agricultural sector has recently started to deploy sophisticated AgriDSS to improve productivity and ameliorate the agricultural supply chains' performance and resilience (Sharma, 2021). Various AgriDSS that use AI have been developed for farm management, manure management, crop production, pest management, irrigation, yield and cultivar selection, and disease control (Van Meensel et al., 2012). These technologies are applied to curb the agricultural carbon footprint and promote sustainable farming modes (Banjeree, 2020; Sharma, 2021). Sustainable agriculture is defined as an "integrated system of plant and animal production practices having a site-specific application that will, over the long term: (a) satisfy human food and fiber needs; (b) enhance environmental quality; (c) make efficient use of non-renewable resources and on-farm resources and integrate appropriate natural biological cycles and controls; (d) sustain the economic viability of farm operations, and (e) enhance the quality of life for farmers and society as a whole" (U.S. Congress, 1990). Decision-making is an integral part of efficient and sustainable agricultural practices, and AI applications have provided promising results regarding the accuracy and robustness of decision-making (Banjeree, 2020; Ferrari et al., 2022). The positive outcomes arise because AI techniques can capture the intricate details of specific conditions, provide the best fit for problems, and solve complex problems (Nishant et al., 2020). AI has effectively contributed to reduced water usage, chemical applications, food waste, and carbon emissions (Abbasi et al., 2022). Thus, AgriDSS can enhance the efficacy of decision-making in agricultural practices and help address the complex, interconnected requirements that define agricultural sustainability.

However, the potential of AI applications in agriculture is not adequately realized due to several issues. In particular, we note that there are concerns that AI models remain obscure, enclosed within a black box, and hidden behind the software, resulting in an opaque algorithmic decision-making process (Dara et al., 2022). General unawareness of AI and economic constraints also limit its anticipated benefits (Cravero et al., 2022; Rao et al., 2021). Due to the growing interest in AI in agriculture, now is an ideal time to evaluate the accumulated knowledge and offer direction to IS researchers. In light of this, we conduct a scoping literature review to enhance our understanding of the challenges and opportunities presented by artificial intelligence in the agricultural context, as described in the following section.

3 Methodology

We conducted a scoping review on AgriDSS for sustainable agriculture. A scoping review is used when knowledge synthesis is needed to map key concepts and identify gaps in a defined study field (Arksey & O'Malley, 2005). It provides the opportunity to identify sources of evidence to inform practice, policymaking, and research (Daudt et al., 2013). As we wanted to broadly survey the existing literature across disciplines with more expansive search criteria, a scoping review was deemed appropriate compared to a systematic review. Much like systematic reviews, scoping reviews are rigorous in their methodology, provide a detailed overview of current research and allow the identification of knowledge gaps in the body of evidence (Munn et al., 2018). Unlike systematic reviews, scoping reviews aim to provide a wide set of perspectives and do not undertake a quality assessment or risk of bias analysis of the included literature (Arksey & O'Malley, 2005). Our review aimed to answer two questions:

RQ1: What are the key research themes in using AgriDSS for sustainable agriculture?

RQ2: What are the roadblocks to the use of AgriDSS for sustainable agriculture?

We followed the four-step process suggested by Paré et al. (2016) for a rigorous literature search and selection process. To identify relevant articles, we initiated a keyword-based search in four databases: Google Scholar, IEEE Explore, ACM digital library, and Web of Science, in August 2022. These databases were selected because they produce a curated set of documents and have received considerable attention as a method for literature searches by researchers (Bakkalbasi et al., 2006; Haddaway et al., 2015). Search terms were built around two core concepts of our study: AI-supported AgriDSS and agricultural sustainability. The details of the keywords and the number of results from each database are provided in Table 1.

Table 1. Initial Database Search Queries and Results

Database	Count	Search query
Google Scholar	662	*"agri" "DSS" OR "intelligent DSS" "climate change" OR "sustainability" OR "net-zero environment" "artificial intelligence"* *"agri" "DSS" OR "intelligent DSS" "climate change" OR "sustainability" OR "net-zero environment" "artificial intelligence" "context awareness"* *"agri" "DSS" "climate change" OR "sustainability" AND "ARTIFICIAL INTELLIGENCE"*
Web of Science	911	*agri* (All Fields) and intelligent DSS (All Fields) and sustainability (All Fields)* *agri* (All Fields) and intelligent DSS (All Fields) and sustainability and context awareness (All Fields)* *AI*, agri* (All Fields) and "DECISION SUPPORT SYSTEM" (All Fields) and "climate change"* *AI*, agri* (All Fields) and "DECISION SUPPORT SYSTEM" (All Fields) and "environment"* *AI*, agri* (All Fields) and Decision support system (All Fields) and climate change* *AI*, agri* (All Fields) and Decision Support System (All Fields) and net zero* *Artificial intelligence (All Fields) and Decision support system (All Fields) and climate change*
IEEE Explore	114	*artificial intelligence* AND DSS AND "climate change" AND farm** *artificial intelligence* AND DSS AND "sustainability" AND agri**
ACM digital library	2011	*agri∗, farm∗, agro∗ AND "artificial intelligence" OR "intelligent dss" AND "sustainability" OR "climate change" AND "decision support system"* *agri∗, farm∗, agro∗ AND "artificial intelligence" OR "intelligent dss" AND "sustainability" OR "climate change" AND "decision support system" AND "context awareness"*

Results were limited to English language articles. All papers identified in the databases except Google Scholar were downloaded and imported to a spreadsheet for screening titles, abstracts, and keywords. For Google Scholar, the identified articles were downloaded and individually screened. A systematic approach was used to search the grey literature as we looked for relevant reports and articles published by the Food and Agricultural Organization of the United Nations (FAO) and the World Bank because these agencies are active in sustainability and agricultural innovations. We searched the grey literature using the keywords AI, artificial intelligence, agriculture, context awareness, holistic solutions, user-centered, and farms on their respective websites. Initially, 3698 articles were retrieved from the four databases and 1001 articles from FAO and World Bank websites. After removing 392 duplicates, the title and abstract of the remaining 4307 articles were screened following Bandara et al. (2015). We focused on plant-based agriculture; thus, articles related to livestock, dairy, waste management, aquaculture, fisheries, and non-agricultural supply chain were removed. Abstracts that referred to different AI techniques, such as machine learning (ML) deep learning, neural network, expert systems, multi-agent systems, and robots, were also selected. In this step, 3480 articles were excluded. More specific inclusion and exclusion criteria were applied to the remaining documents (Table 2), leaving 51 scientific articles and 13 grey literature documents.

Table 2. Inclusion and Exclusion Criteria

Inclusion criteria The inclusion criteria are based on the defined research questions and the aims of the study.	1) empirical and conceptual articles primarily centered around the application of different AI techniques in agricultural activities, 2) articles that discuss smart and digital farming with a detailed description of AI use in agricultural activities, 3) articles focusing on agricultural sustainability, 3) articles related to AI research that used or applied AI techniques such as robots, computer vision, and automation, 4) reports from FAO and World Bank on AI and agriculture, 5) articles on AI risks, ethics, and responsible AI in the agricultural sustainability context.
Exclusion criteria The exclusion criteria are based on the defined research questions and the aims of the study.	1) articles focused on livestock, dairy, waste management, aquaculture and fisheries, non-agricultural supply chain, 2) IoT and big data articles that suggested AI and ML as supportive tools for precision farming, 3) books, dissertations with general references to AI use in agriculture, 4) bibliometric analysis and systematic literature reviews that were primarily descriptive, capturing the trends of publications and did not align with our research questions (i.e., use and application of AI in agricultural activities), 5) technical articles which did not relate to sustainability and were primarily based on the design of AI algorithms.

We then conducted a backward and forward search on all 64 articles to identify other relevant articles. Backward and forward searches found 34 and 23 articles, respectively, creating a final sample of 121 documents (Figure 1).

Data extraction was done in Microsoft Excel. The elements of data extraction were types of publication (conference proceedings, magazines), year of publication, type of AI technique used for agricultural operations, sustainability focus, results specific to the use of AgriDSS, and other challenges related to the use of AgriDSS. The quality appraisal of the retained documents was not conducted.

Once selected, each article was read multiple times to ensure the accuracy of the information drawn from it. We analyzed the sample through open coding followed by axial coding. We inductively generated the categories and subcategories while engaging with the body of literature (Locke et al., 2020) and then coded the ideas from the studies accordingly (Bandara et al., 2015; Webster & Watson, 2002). Next, we conducted selective coding by comparing and linking identified categories. Figures 4 and 6 illustrate the final aggregation of key codes regarding RQ 1 and 2 and how relevant concepts were developed. Data coding for the 121 articles was done using Microsoft Excel by the first author to ensure consistency. The coding outcomes and the uncertainties during the coding procedure were specified and discussed with the second author during successive meetings.

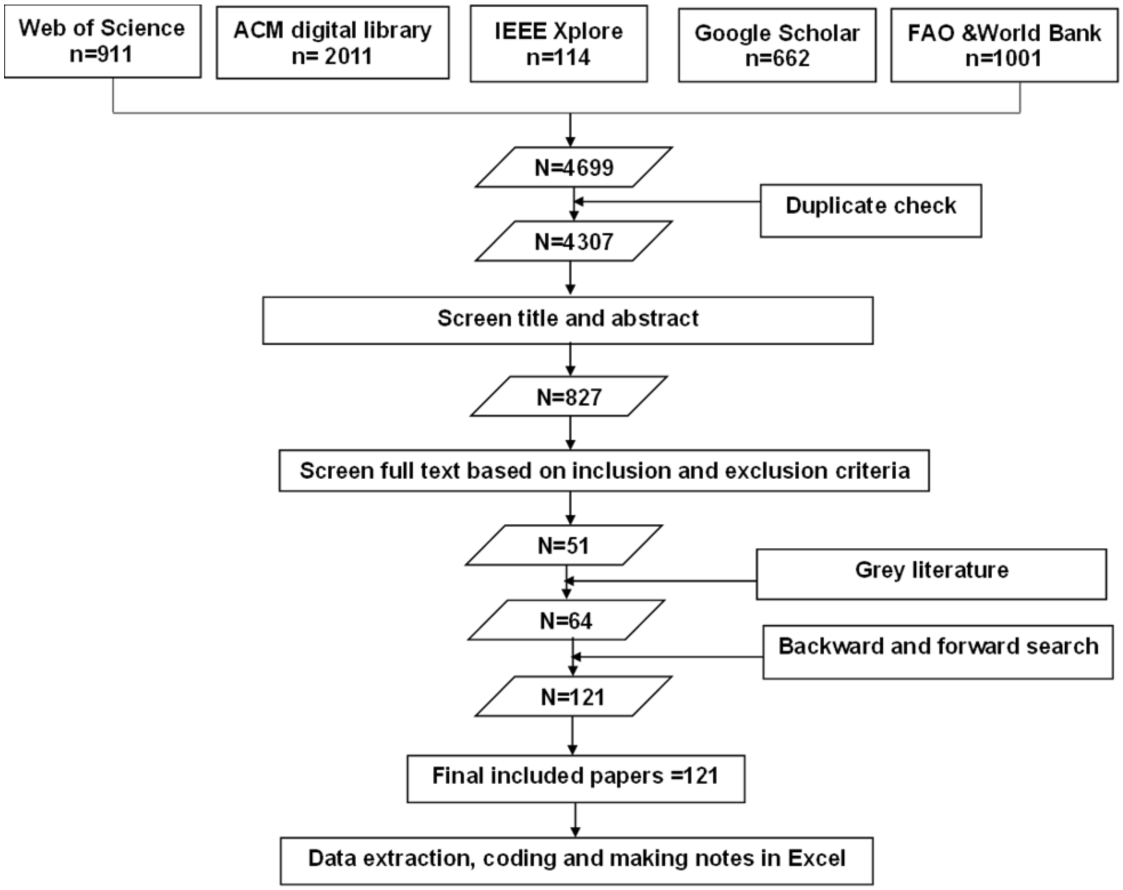

Figure 1. Search and Selection Process of Articles

The authors discussed the coding rationale to refine the results and achieve a consensus on using a theme code that best represented each paper's goals, directions, and outcomes. An independent research assistant coded 13 articles (about 10 percent) to validate the results, resulting in 90.4% inter-rater reliability, which suggested valid coding (Belur et al., 2021) and shared understanding within the coding team. Four rounds of coding were done to arrive at the final themes (five for RQ1 and four for RQ2). The coding results for all nine themes are presented in the Appendix (Tables A1-A11).

4 Findings

Of the 121 papers, the majority were published in computer science (31), followed by agriculture (30), engineering (21), and IS (10) disciplines. Other disciplines covering the topic were AI, food science, chemistry, environmental science, geo science, biotechnology, medicine, meteorology, physics and management, and operations research (see Figure 2).

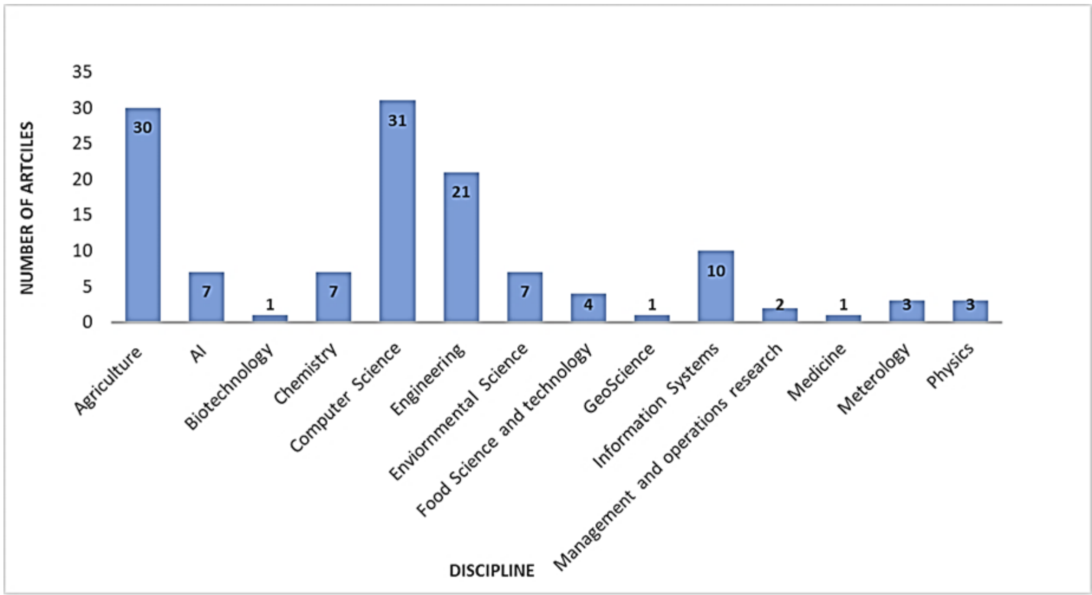

Figure 2. Distribution of the Included Articles in Different Disciplines

The documents were published between 2006 and 2022, with the highest number of publications in 2022 (see Figure 3), even considering that the sample does not include articles published after November 2022. The plausible reasons for the increase in articles could be the increasing attention on SDGs, and the food and supply chain crisis spurred due to the COVID pandemic and geopolitical reasons. The findings related to the two research questions are discussed in the following subsections.

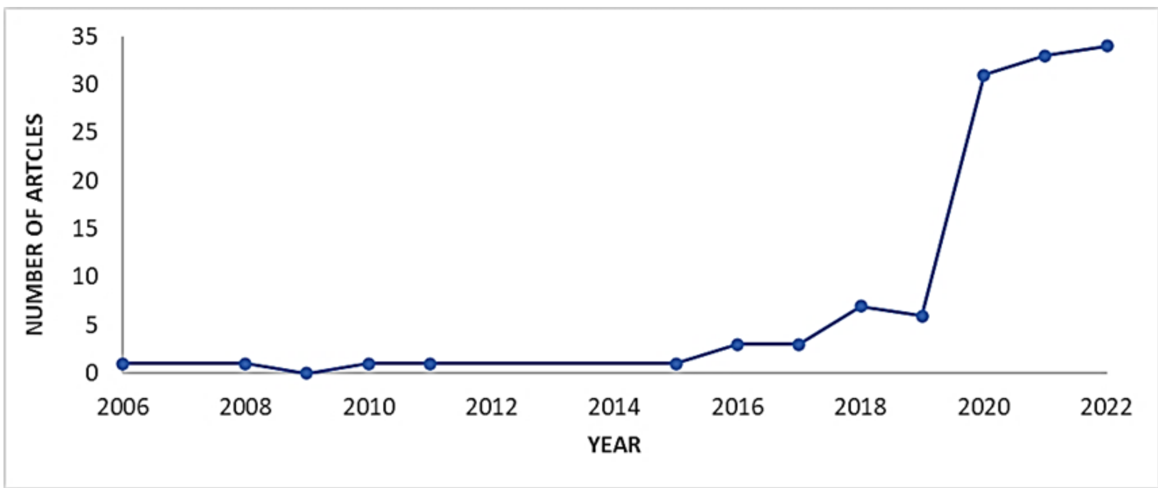

Figure 3. Distribution Based on Year of Publication

4.1 What are the Key Research Themes in Using AgriDSS for Sustainable Agriculture?

Our analysis reveals five main themes in the literature: AI resources, AI capabilities, types of agricultural tasks, task augmentation, and human-AI complementarity, as illustrated in Figure 4.

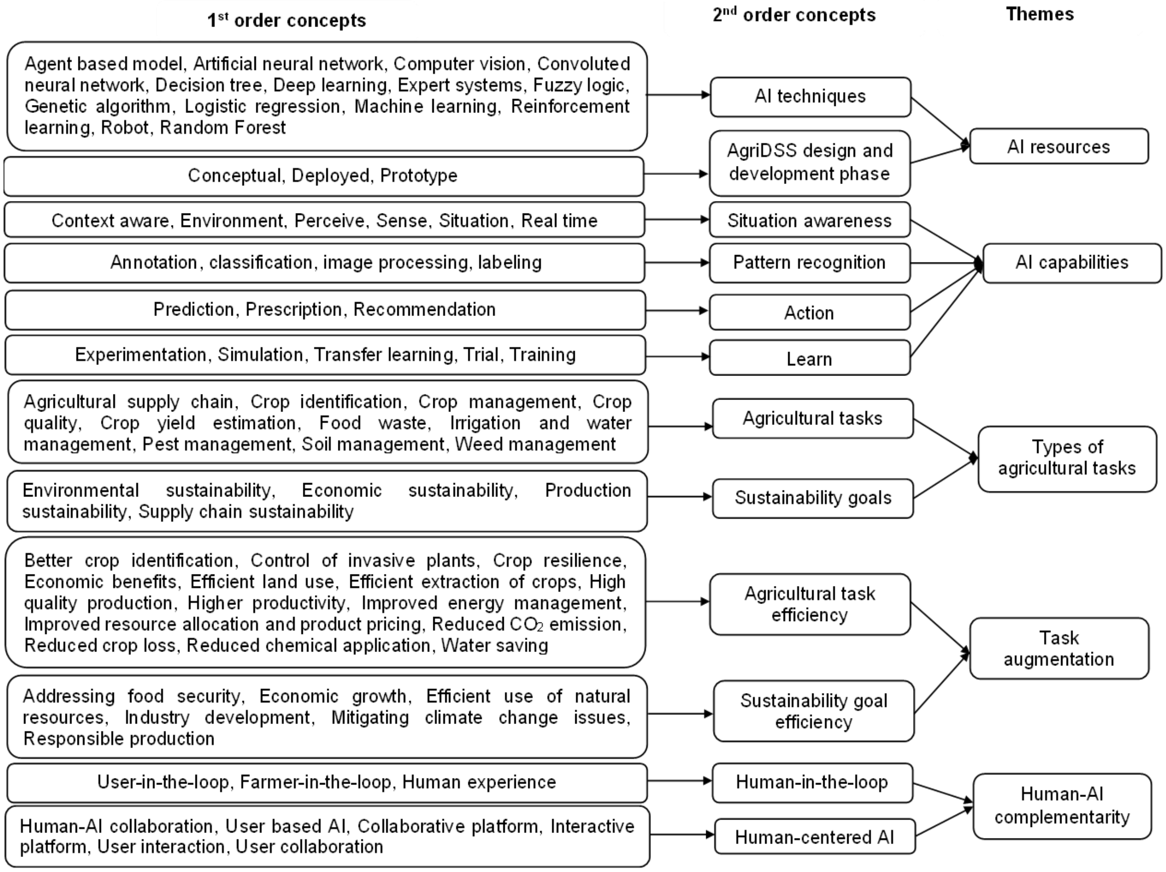

Figure 4. Final Aggregation of Open, Axial and Selective Codes for RQ 1

4.1.1 AI Resources

AI resources comprise physical resources infrastructure, databases, networks, software packages, and applications that enable data collection and analysis (Abbasi et al., 2022). The literature focuses on two types of AI resources: AI techniques and AgriDSS artifacts under different design and development stages. Diverse AI techniques, such as ML, neural networks, deep learning, expert systems, computer vision, robots, and cognitive computing, are used for agricultural tasks and services (see Appendix Table A1). ML applications are widely used in agricultural tasks that do not require complex decision making and are routine activities (Khan et al., 2022; Mugiyo et al., 2021; Ridwan et al., 2021). For solving complex problems, which require more time, effort, and information processing (detection, location, and classification), deep learning, a more developed form of ML, is being applied (Dhanya et al., 2022; Fenu & Malloci, 2022; Fiehn et al., 2018; Ofori & El-Gayar, 2020). Expert systems are reported to be an efficient tool for complementing agricultural workers' decision-making (Bhat & Huang, 2021, Chamara et al., 2020; Hungilo et al., 2019). Autonomous vehicles, agent-based systems, and robots are also evident in complementing existing farm-level models and driving sustainable agricultural practices (Abbasi et al., 2022; Dorin et al., 2022; FAO, 2018; Fikar, 2018). Additionally, the digital twin as a virtual, real-time equivalent of AgriDSS is being actively explored in the agricultural domain to boost the effectiveness and efficiency of agricultural supply logistics (Galaz et al., 2021; Kugler, 2022; Linaza et al., 2021).

The other type of AI resource evident in the literature is the AgriDSS artifact being developed or used for agricultural activities. AgriDSS go through different design and development phases before they are commercially available. The literature presents examples of AgriDSS at different development stages: a real-life application of AgriDSS (deployed), AgriDSS under design, test, or simulation (prototype), and a conceptual model of AgriDSS. We consider these as AI resources because these are assets (proposed, developed, or under development) that could eventually find application in effective agricultural operations. Most AgriDSS discussed in the literature are conceptual and refer to crop management activities (Figure 5). AgriDSS, particularly those built on more advanced AI techniques, such as deep learning, artificial neural network, and convoluted neural network, are in the prototype phase developed for irrigation and water management. Very few papers discussed AI designs that were actually deployed in real farm operations for disease management and were typically case studies or field experiments (Fenu & Malloci, 2021; Magalhães et al., 2022).

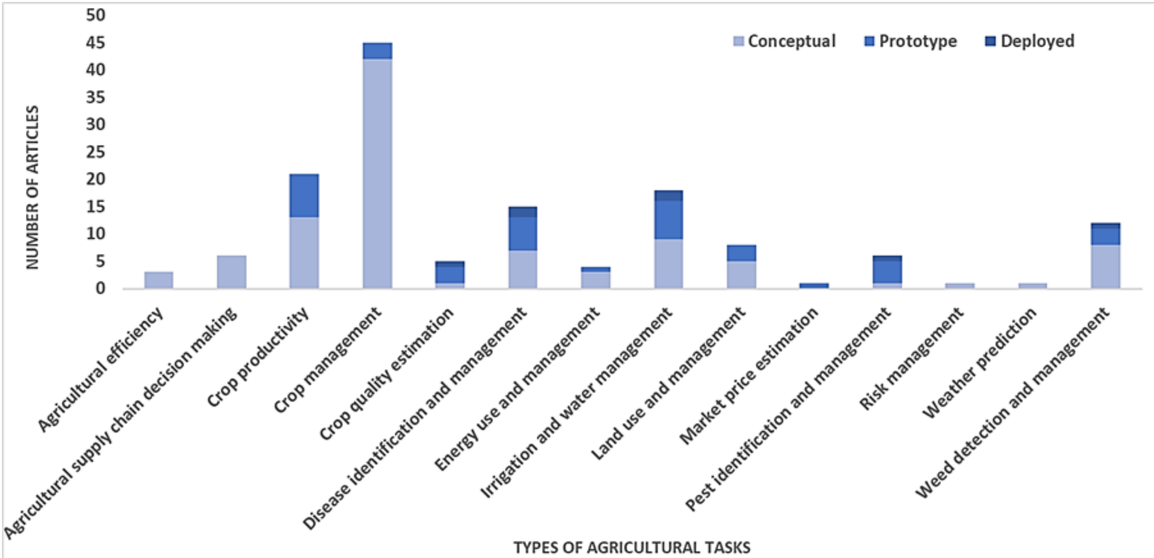

Figure 5. Distribution of Articles Based on Types of Agricultural Tasks and AgriDSS Development Phase

4.1.2 AI Capabilities

The basic capabilities of AI relate to its ability to perceive the environment and identify data, recognize patterns in the data, take actions in the form of prediction, prescription, and recommendations, and then adapt its expertise based on the success or failure of those actions (Cravero et al., 2022; Jagatheesaperumal et al., 2021). AgriDSS demonstrates situation awareness by perceiving the context and understanding the situation triggered by events in real-time (Benos et al., 2021; Cravero & Sepúlveda, 2021; Liu et al., 2020). Situation awareness enables the accuracy of the predictions and recommendations of AI resources (Abioye et al., 2022; Cravero & Sepúlveda, 2021, Rao et al., 2021). Most articles report that the prediction accuracy of AgriDSS is necessary for gaining beneficial outcomes for agriculture (see Appendix Table A2). Some studies, however, report the failure of AI recommendations when applied to settings different from experimental settings (Fenu & Malloci, 2022; Chandra & Collis, 2021). Prediction accuracy of AgriDSS improves when AI techniques are integrated with other resources, such as computer vision, robots, and sensors (Cravero & Sepúlveda, 2021; Hungilo et al., 2019; Kamyshova et al., 2022). Transfer learning, a subset of ML, has been suggested as an appropriate means to improve the adaptation of AgriDSS in a new task and environment (Wang et al., 2022).

4.1.3 Types of Agricultural Tasks

The third theme captures the variety of agricultural and sustainability tasks (see Appendix Table A3) for which AI resources are actively used (Bahn et al., 2021; Concepcion et al., 2021; Santos Valle & Kienzle, 2021). AI resources are widely applied in crop management activities that include agricultural practices of crop planting, growth monitoring, harvesting, and assessing overall production efficiency (Concepcion et al., 2021; Ferrari et al., 2022). AI resources are also commonly applied for pest and disease management, weed management, crop identification, irrigation and water management, crop yield estimation, crop quality assessment, soil management, and maintaining the agricultural supply chain (Fikar, 2018; Kumar et al., 2020; Newlands et al., 2019; Panchbhaiyye & Ogunfunmi, 2018). The literature contains studies on the development and field testing of prototypes for price prediction and estimation of harvest time, weed management, and irrigation scheduling (Figure 5) (Kim et al., 2022; López-Correa et al., 2022; Ooge & Verbert, 2022). AgriDSS, in the form of mobile apps and agro-weather tools, have also been deployed for weather and disease detection (FAO, 2018).

Another important category of agricultural tasks is achieving sustainability goals in terms of social, economic, and environmental sustainability (Everingham et al., 2016; Fikar, 2018; Newlands et al., 2019). Sustainable agriculture practices enrich agricultural productivity and reduce harmful environmental impacts by reducing food wastage, chemical application, and soil, air, and water contamination (Fikar, 2018; Sharma, 2021). AI applications for sustainability are viewed as examples of technological niche innovations capable of upscaling social, economic, and environmental sustainability initiatives (Galaz et al., 2021). Deep learning has been used in assessing the pesticide risk in the air, water, and soil, land use management, and CO_2 emissions allowing farmers to make informed decisions regarding pesticide application in the field (Heldreth et al., 2021; Nguyen et al., 2021). Agent-based simulations and dynamic routing procedures are proposed to avoid food losses from mismanaged inventory distributions (Fikar, 2018).

4.1.4 Task Augmentation

In the AI literature, task augmentation occurs when the output derived from AI resources is embedded in structured decisions that augment human capabilities and support humans in everyday tasks (Atwal et al., 2021; Dhanya et al., 2022; Panchbhaiyye & Ogunfunmi, 2018; Singh, 2018). Thus, the task augmentation theme includes articles on the value creation of AgriDSS by targeting more efficient and effective decision-making and highlighting the benefits of using AI resources for specific tasks (see Appendix Table A4). This theme comprises two second-order concepts; agricultural task efficiency and sustainability goal efficiency. Farmers receive advice or instructions from a predictive or prescriptive AI model, which is then used to improve their decision-making capabilities (Schöning & Richter, 2021). In this way, the underlying value creation mechanism is the augmentation of farmers' information processing and decision-making capabilities through AI to improve task efficiency and reduce manual labor (Concepcion et al., 2021; Dhanya et al., 2022; Zhang et al., 2020). Agricultural task efficiency is evaluated in terms of efficient agricultural operations, timely irrigation, planting and harvesting, efficient supply chain, and economic benefits (Banjeree, 2020; Bahn et al., 2021; Saheb et al., 2022).

Augmentation, in the literature, is also evident in how AgriDSS enhances the attainment of sustainability goals. AgriDSS play a vital role in sustainability goals efficiency by monitoring and maintaining the sustainability of the agricultural sector through timely predictions of CO_2 emissions and rainfall, reducing waste, and recommended use of pesticides and weedicides (Dhanya et al., 2022; Mugiyo et al., 2021; Ridwan et al., 2021; Sharma et al., 2021). Such mechanisms effectively increase the sector's productivity and contribute to conserving natural resources such as soil, land, and water (Bahn et al., 2021; Ridwan et al., 2021). The "solution space" of AI can be applied to the "problem space" of climate change resulting in significant benefits by helping to understand the problem and by facilitating effective responses (Cowls et al., 2021). Furthermore, the literature points towards the contributory role of AI in attaining the SDGs related to eliminating poverty, establishing food security, ensuring responsible consumption and production, tackling climate action, and preserving the quality of life on land (Banjeree, 2020; Fikar, 2018; Trabelsi & Bel Hadj Ali, 2022).

4.1.5 Human-AI Complementarity

The fifth theme highlights the complementarity of humans and AI systems for boosting sustainable agriculture practices and includes two second-order concepts: human-in-the-loop and human-centered AI (see Appendix Table A5). The research uses different terms to present the interactions between humans and ML algorithms, such as human-in-the-loop, farmer-in-the-loop, and user-in-the-loop (Dara et al., 2022; Holzinger et al., 2022; Schöning & Richter, 2021), which we grouped under the umbrella term of human-in the-loop in second-order concepts. Human-in-the-loop is the process of combining machine and human intelligence to acquire beneficial outcomes in the long term (Dara et al., 2022; Holzinger et al., 2022; Jagatheesaperumal et al., 2021). In the agricultural context, this means including farmers' experiences to improve ML model accuracy, speed, and context awareness while simultaneously enhancing human efficiency and efficacy (Schöning & Richter, 2021; Viani et al., 2017). Creating AI models and solutions while engaging all stakeholders (farmers, system designers, developers, policymakers) and integrating their experiences can bring more precision to agricultural decision making (Holzinger et al., 2022; Kalyanaraman et al., 2022; Schöning & Richter, 2021; Viani et al., 2017).

Human-centered AI (HCAI), which learns from human input and collaboration, is a potential driver in enhancing AgriDSS efficacy (Holzinger et al., 2022). HCAI is a synergistic approach that aligns AI solutions with human values, ethical principles, and legal requirements to ensure safe, secure, and trustworthy AI (Holzinger et al., 2022, Schöning & Richter, 2021). HCAI focuses on amplifying farmers' performance by designing appropriate and collaborative user interfaces for AI-supported offerings. "Farmer-centered design" involves a dynamic understanding of farmers' changing needs and challenges to avoid parachuting solutions. Supporting inputs from farmers on soil, fertilizer, and pesticide treatment through a cloud-based scalable collaborative platform and web-based expert interface, along with publicly available datasets, can augment image database and training data to improve AgriDSS model accuracy (Singh, 2018; Sparrow et al., 2021).

4.2 What are the Primary Roadblocks to the use of AgriDSS for Sustainable Agriculture?

The literature discusses twelve roadblocks to the use of AgriDSS for sustainable agriculture, which are grouped into four main themes social roadblocks, systems roadblocks, deployment roadblocks, and ethical roadblocks (Figure 6).

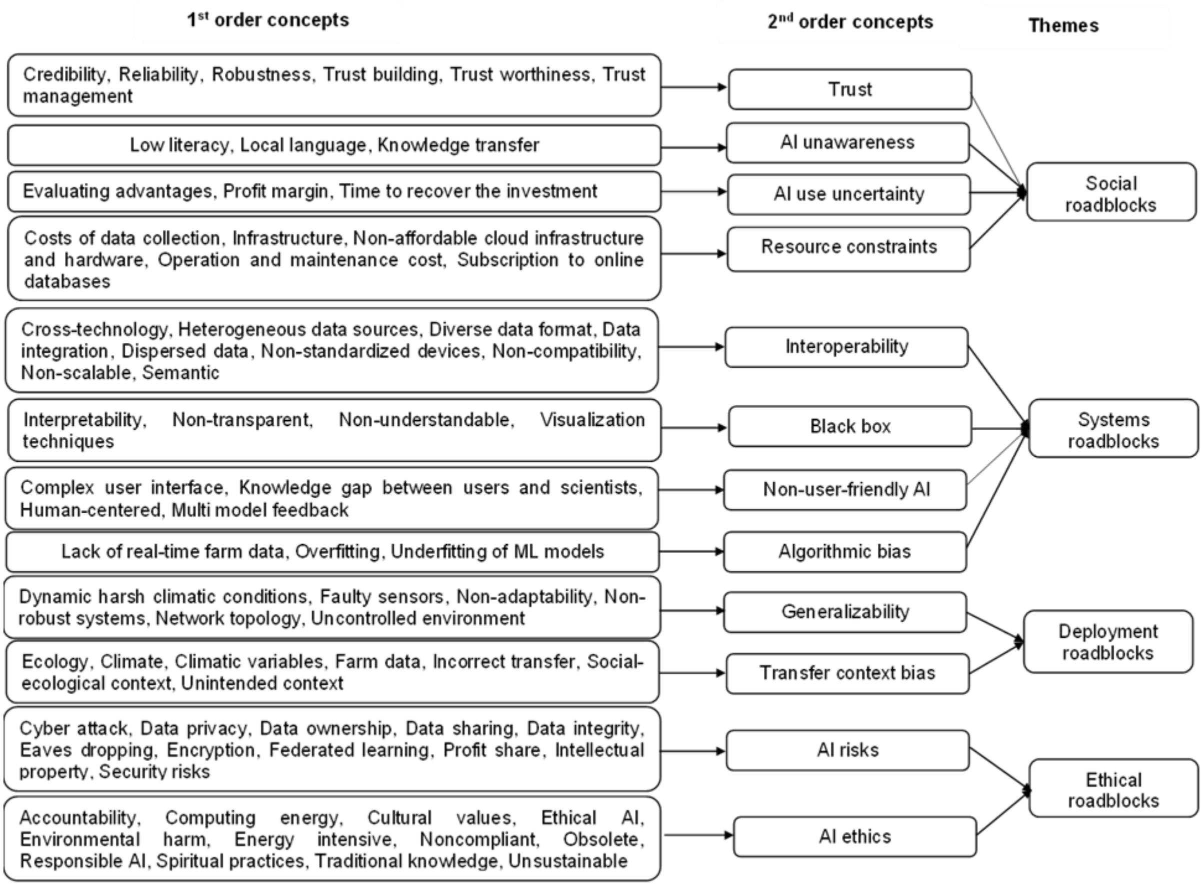

Figure 6. Final Aggregation of Open, Axial, and Selective Codes for RQ 2

4.2.1 Social Roadblocks

We conceptualize social roadblocks as barriers related to the conditions in which individuals work, live, and interact with others that create hindrances in using AgriDSS. The literature discusses four primary social barriers: trust, AI unawareness, AI use uncertainty, and resource constraints (see Appendix Table A6). First, the use of AgriDSS for sustainable agriculture is influenced by trust (Abbasi et al.,2022; Dara et al., 2022). Because AI-informed judgments affect interconnected systems with living and non-living creatures, and the effects of incorrect decisions are difficult to reverse, it is challenging to establish trust in the effectiveness of AI in agriculture (Abbasi et al., 2022). The lack of trust in AgriDSS is largely due to the relative lack of evidence supporting the effect of AI on agricultural output, the lack of openness and unregulated norms surrounding data sharing, and farmers' unease with sharing farm data with technology companies. These factors can inhibit farmers' willingness to implement and continue using AI solutions (Abbasi et al., 2022; Abioye et al., 2022; Dara et al., 2022). Lack of trust is also reflected in the established belief systems and normative roles between farmers and agribusinesses (Heldreth et al. 2021). For instance, farmers believe in unequal power relations between farmers and large businesses and do not trust external organizations, resulting in diminished use of AgriDSS.

Second, farmers' unawareness of new, upcoming technologies and their benefits to the agricultural sector threaten the efficient use of AgriDSS for sustainable agriculture (Abbasi et al., 2022). AI awareness is vital for gaining agricultural efficiency, and a lack of knowledge of AI and its applications can be the reason behind the slow pace of digitization of the agricultural sector (Chamara et al., 2020; Chandra &Collis, 2021; Hassan et al., 2021). Most farmers have no or minimal idea about the significance of AI, how to implement and use AgriDSS, and which technology is suitable for their farm and meets their requirements (Benos et al., 2021; Hassan et al., 2021; MacPherson et al., 2022; Ooge & Verbert, 2021).

The third social roadblock relates to AI use uncertainty. AI use uncertainty refers to situations where farmers are not confident about the financial upside potential of AgriDSS usage (Abioye et al., 2021). Farmers are interested in the return on investment for adopting ML applications. However, inadequate information on return on investment discourages farmers from investing in ML applications and deploying them for agricultural tasks (Abioye et al., 2021; Cravero et., 2022). In addition, the functionalities included within AgriDSS are sometimes complicated and lack direct applicability to the intended users and their activities (Ooge & Verbert, 2021; Spanaki et al., 2022b).

The fourth social roadblock in deploying and using AgriDSS to improve sustainable agriculture relates to resource constraints in the form of farm size, infrastructure, and finance, particularly for small-scale farmers (Abioye et al., 2021). Studies suggest that the high cost of sensors, actuators, cloud infrastructures, and limited access to internet connectivity are potential barriers to the effective use of AgriDSS (Helderth et al., 2021; Sharma et al., 2021). Despite the increase in the availability of cloud infrastructures and the reduction in the cost of ML applications, these resources remain unaffordable for small-scale farmers (Kalyanaraman et al., 2022; Sharma et al., 2021). Besides the cost, small individual farms situated in remote areas have limited access to the internet, infrastructure, and investment capital (Helderth et al., 2021; Kalyanaraman et al., 2022).

4.2.2 Systems Roadblocks

The second theme, systems roadblocks, includes four challenges that arise due to the technological attributes of the AI systems (see Appendix Table A7).

First, AI systems do not work in isolation and depend on other digital solutions, including software tools and services for data collection. Interoperability among software tools, hardware, or processes/protocols is often limited because of the lack of established standards (Dadi et al., 2021; Jagatheesaperumal et al., 2021; Metta et al., 2022). Standardization of devices is essential for the complete utilization of technology for more comprehensive agricultural tasks (Abioye et al., 2022; Chandra & Collis, 2021). However, there is little concern about integrating open data repositories and using standards and formats that allow the exchange of information and interoperability (Cravero & Sepúlveda, 2021; Dara et al., 2022; Kour & Arora, 2020). Non-integration of crop-sensing devices and developed models threaten effective and timely decisions (Cravero et al., 2022; FAO, 2020; Saiz-Rubio & Rovira-Más, 2020).

A second concern is the black-box nature of AgriDSS, which makes algorithmic decision making an opaque process for farmers. The opaqueness of AgriDSS makes it difficult for farmers to interpret and understand the AgriDSS outputs, often leading to the misinterpretation of recommendations (Linaza et al., 2021). Inaccurate recommendations can have repercussions regarding unsustainable practices and economic loss on the farm and cause reduced acceptance and use of AgriDSS (Ryan, 2022). Interpretable and explainable models diminish the black-box nature of AI, enable understanding of the reasons behind any specific decision, and promote the acceptance of AgriDSS (Dara et al., 2022, Ryan, 2022). Ooge and Verbert (2022) suggest that improved model transparency with tailored explanations and designed visualizations can foster user trust and acceptance of AI.

Third, we found non-user-friendly AI technologies as barriers to gaining agricultural efficiency (Trendov et al., 2019). For example, AI tools cannot provide actionable recommendations to help farmers if the system is complicated or defective in design and usability (Dara et al., 2022). A farmer-friendly AgriDSS assists real-time communication between farmers and experts with an easy-to-use interface design and includes features that permit easy communication and comprehension by farmers (Abioye et al., 2022). Developing an AI model that considers the native language and the cultural norms of farming communities and users can increase the efficacy of interaction between farmers and AgriDSS (Helderth et al., 2021; Kour & Arora, 2022). Flexibility in the operational process and trouble-free operation of AI systems make systems more friendly and easier to use (Kour & Arora, 2020; Mohr & Kühl, 2021).

A fourth systems-related challenge encountered with AgriDSS is their potential for bias (Abbasi et al., 2022; Abioye et al., 2022). Biases in algorithmic models can be due to misinterpretation and contamination of input data (Abioye et al., 2022; Cowls et al., 2021) and selection bias in data collection (Dara et al., 2022). Common problems with training for ML are the underfitting and overfitting of trained models. Underfitting scenarios denote high bias and low variance, inferring that a trained model has not learned the data, while overfitting indicates poor performance with unseen (test) data (Abioye et al., 2022). Both these issues can be detrimental to agricultural decisions leading to unfavorable results, like delays in the plantation, harvest, and crop loss due to poor decisions, which may make farmers reluctant to continue using AgriDSS (Dara et al., 2022; Galaz et al., 2021).

4.2.3 Deployment Roadblocks

The third theme, deployment roadblocks, includes two primary challenges that emerge during the application and implementation of AgriDSS in the field and create barriers to their effective use: the lack of generalizability and transfer context bias (see Appendix Table A8).

One of the major problems with AgriDSS is that, during their design and development process, the dynamism of the agricultural context is often ignored (Dhanya et al., 2022; Fiehn et al., 2018; Galaz et al., 2022). This occurs because the designs of AgriDSS are influenced by an incomplete understanding of the context and flawed perceptions of programmers and systems designers (Galaz et al., 2022) drawn on laboratory results or field experiments in controlled environments. As a result, these artifacts are highly sensitive to varying spatial and temporal field conditions and are limited in addressing a wide range of eventualities that occur in real settings (Bestelmeyer et al., 2020; Bhagat et al., 2022) such as when AgriDSS is put into practice under real settings, making the generalizability of AgriDSS predictions challenging (Chandra & Collis, 2021; Wang et al., 2022). Sophisticated computer vision models in various agricultural use cases often do not perform as expected in production environments (Dhanya et al., 2022). Failure to generalize AgriDSS results is a frequent barrier when geographically specific, and context-specific, data are not included in the training of AgriDSS models and may impede farmers from using AgriDSS.

Transfer context bias is another potential barrier when algorithmic models developed in particular socio-ecological and climate conditions are used in other contexts. For example, the AgriDSS model designed for agricultural activities will reflect biased results when deployed in a forestry context (Galaz et al., 2021). Unlike algorithmic bias that arises due to incomplete training data sets or unrepresentative data, transfer context bias emerges due to variation in the ecological conditions. Hence, we consider transfer context bias as a deployment challenge rather than a systems challenge because despite the suitability of training data and resulting model for the initial socio-ecological condition (e.g., big farm in rich data context), using it in a different setting (e.g., small farm) could cause damaging results. Such bias may emerge, for example, as individuals and companies use off-the-shelf AI software for their purposes (Galaz et al., 2021). Under the circumstances, when both the training data and the applied context are appropriate, misalignment between algorithm prediction and user needs can cause inappropriate application of predictions (Bhagat et al., 2022).

4.2.4 Ethical Roadblocks

Under the theme of ethical roadblocks, we include two second-order concepts: AI risks and other ethical issues that plague the real-world usage of AI in agriculture (see Appendix Table A9). Risk in the context of AI is defined as the probability of the harmful event occurring multiplied by the loss the event could generate (Buehler et al., 2022). First, we found that the risks of data privacy and ownership are inherent to AgriDSS use. Because of the availability of diverse data sources in intelligent farming systems, including personal and business data, privacy is paramount (MacPherson et al., 2022). Farmers are concerned about corporations owning, sharing, and selling their data without their consent or awareness (Dara et al., 2022). A privacy-preserving, secure, and sovereign data-sharing platform can help aggregate data to create market linkages and deliver AI-based advisories (Chandra & Collis, 2021). Another associated risk prevalent in the literature was cybersecurity (Abioye et al., 2021). Modern and advanced technologies create an ecosystem of remotely accessible devices, allowing adversaries to plan cyberattacks such as eavesdropping, data integrity, denial-of-service attacks, or other disruptions that could be detrimental to agribusiness (Araújo et al., 2021; Dadi et al., 2021). Such cyberattacks risk the privacy, integrity, and availability of the system by stealing information (products, financial decisions, and future plans) or carrying out disruptive actions (damaging the products and equipment) on the intelligent farming systems

(Chandra & Collis, 2021; Galaz et al., 2021). Appropriate mechanisms such as data encryption and access control can ensure security requirements and data protection (Abioye et al., 2022).

Second, we found other ethical issues related to AI responsibility and accountability as hindrances in AgriDSS use. The problem with available automated decision-making AI models is the lack of legal and policy clarity on the accountability for the repercussions of the mismanagement, errors, or wrong decisions/recommendations made by the AI systems (Dara et al., 2022; Marvin et al., 2022). This concern is especially important when users interact with robots regarding safe interaction with humans and user well-being (Bhagat et al., 2022). Furthermore, AgriDSS misjudgments can jeopardize long-term agricultural outcomes. For example, incorrect recommendations can result in excessive or insufficient fertilizer application, resulting in crop loss and degradation of natural resources (soil). Amid concerns about rising carbon emissions from computing power and data center maintenance, the threat of AI failure raises questions about whether introducing AI will backfire and cause more harm than good to the environment, threatening the effective use of AgriDSS (Dhanya et al., 2022). The omission of cultural and spiritual practices in the design and development of AgriDSS can also further exacerbate the challenges to AgriDSS use because some users have found the AgriDSS to be non-compliant with their needs and traditional practices and reject AI due to cognitive biases (Atwal et al., 2021; Kelly et al., 2022).

4.3 Summary of Findings

In response to our research questions, we found nine themes in the literature. AI resources in the form of AI techniques and AgriDSS design and development phase are applied in carrying out different agricultural tasks, that is, agricultural tasks and sustainability goals. AI capabilities emerged as the driving force for achieving task augmentation in terms of agricultural task efficiency and sustainable goal efficiency. Finally, human-AI complementarity surfaced as an effective way to enhance the performance of AgriDSS. For the second research question, we found four major roadblocks that hinder the effective use of AgriDSS and block their potential to achieve the goals of sustainable agriculture. We found systems and deployment roadblocks as hindering elements in farmers' decision-making processes and reduce their confidence in the usability and credibility of these systems in carrying out farm activities. Social and ethical roadblocks emerged as factors that stopped the willingness of users to adopt and continue using these systems in agricultural activities. In sum, the literature suggests that the use and usefulness of AgriDSS in contributing to sustainable agriculture are hindered at different levels that can be addressed by effective coordination between humans and AI systems where superior intelligence and performance can be achieved when both humans and AI systems work together rather than independently (Abioye et al., 2022). The sample literature emphasizes the importance of involving and collaborating with users and domain experts to maximize the efficiency of AgriDSS, but it does not address how this effective collaboration can be designed and implemented. We propose to address this gap by proposing a conceptual framework that suggests some strategies for generating effective collaboration between humans and AI systems.

5 Development of Conceptual Framework to Guide Future Research

In this section, we consolidate the key findings of the literature review and propose a conceptual framework outlining how the current roadblocks (social, systems, deployment, and ethical) to AgriDSS use can be tackled to achieve sustainable agriculture outcomes (Figure 7). Sustainable agriculture outcomes are defined as ensuring food productivity over time with the minimum negative effect on the environment and supporting the sustainable management of land, water, and soil (Ciempa, 2021). Sustainable agricultural outcomes, in terms of environmental, social, and economic sustainability, can be accomplished if the current challenges are addressed systemically and holistically. One approach in this direction is transforming agricultural workers from passive users to active agents who share their expertise and context-specific knowledge while co-designing the AgriDSS (Kugler, 2022; Viani et al., 2017; Wang et al., 2022;).

Agricultural workers build tacit knowledge structures while i) *gaining experiences* on the farm, ii) *reflecting*, iii) *building abstract concepts* based on these experiences, and iv) *experimenting actively* with these concepts on farms to generate accepted agricultural practices. These four inherently iterative steps comprise the experiential learning cycle, which positively impacts the modelling of individual behavior, improves declarative knowledge retention, and provides individuals with domain expertise (Yi & Davis, 2003). Experiential learning is "the process whereby knowledge is created through the transformation of experience" (Kolb, 1984, p. 41). Learning is achieved through the continuous interaction between prior knowledge and new experiences and takes place in a history-dependent and routine-based incremental way (Clarysse et al., 2013; Kolb, 1984). Experiential learning provides logical reasoning in identifying the cause of complex real-life problems, analyzing the harmful outcomes, reflecting on the probable solutions, and retaining past actions that produce desired results (Mao et al., 2020). Hence, experiential learning has been applied in successfully implementing IS artifacts and robust IS design (Bondarouk, 2006; Jewer & Evermann, 2014; Thouin & Hefley, 2020). Considering the prominence of experiential learning in solving complex problems, we aim to apply experiential learning as a perspective in overcoming the current roadblocks to AgriDSS use and performance.

To do so, we propose a conjoint experiential learning (CEL) (figure 7) framework to incorporate agricultural workers' experiences and knowledge in AgriDSS development. This framework suggests that the current roadblocks to AgriDSS use can be addressed by combining agricultural workers' experiential learning with data-driven AI learning resulting in augmented AgriDSS capabilities, eventually contributing to sustainable agriculture outcomes. In the agricultural domain, workers develop their learning by overseeing the machine's actions and applying them to complete agricultural tasks. The four stages of experiential learning (*gaining experience, reflecting, building abstract concepts, and experimenting actively*) help agricultural workers to develop best field practices. For their part, AgriDSS learn through AI capabilities, that is, repeated cycles of collecting data (*situation awareness*), recognizing patterns within data (*pattern recognition*), and generating predictions (*action*) until sufficient accuracy for the tasks at hand is achieved (*learn*) (Zhang et al., 2022). This accuracy is determined principally by data quality and whether or not the system is retrained with updated data in changing scenarios. We contend that by fostering and facilitating interactions between human experiential learning and data-driven AI learning, learning on both sides can be improved, which will lead to conjoint learning.

Conjoint learning can benefit agricultural workers by developing their technological skills, creativity, and problem-solving aptitudes. Further, AgriDSS will simultaneously benefit from augmented capabilities and scalability. The symbiotic impact of this collective learning can diminish the current roadblocks by creating more accurate, scalable, explainable, and user-friendly systems and promoting effective AgriDSS use.

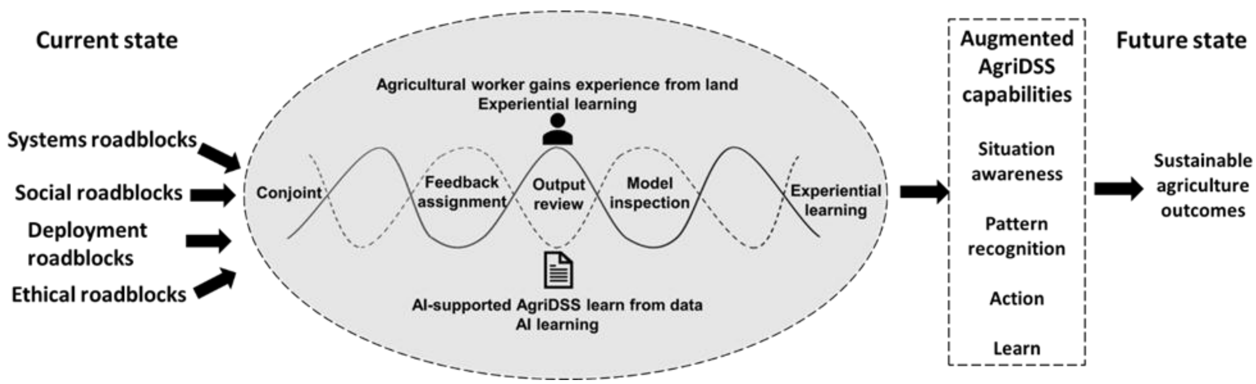

Figure 7. Conjoint Experiential Learning Framework

5.1 Conjoint Experiential Learning Augments AI Capabilities

In this section, we elaborate on conceptual approaches suggested by the literature review that can support the augmentation of AI capabilities and human learning. We further build on these approaches to suggest three distinct strategies that could be used to integrate agricultural workers' experiential learning for augmenting AgriDSS capabilities, eventually leading to AgriDSS performance enhancement. The idea is to incorporate human feedback in the systems so that the systems learn independently, eventually reducing agricultural workers' physical involvement in agricultural activities.

First, the *feedback assignment strategy* calls for employing agricultural workers to assign labels, select features and/or generate new samples. A challenge with training ML algorithms is obtaining quality labeled data because data labeling tasks are becoming increasingly complicated and domain-specific (Holzinger et al., 2022; Schöning & Richter, 2021). The large amount of raw and unstructured streaming data received from different devices and sensors contains multiple dimensions and irrelevant features, which can obscure the relevant feature, making data labeling a daunting task (Suh et al., 2018). Agricultural workers can contribute to improving data labeling accuracy and quality by sharing their rich and keen reflections and observations in data labeling tasks (Schöning & Richter, 2021). For instance, their observations in distinguishing weeds from crops can be applied in selecting the best images representing weeds and feeding the best images into the systems so robot learning can be improved. Data labeling accuracy achieved through agricultural workers' assistance can help improve pattern recognition and the accuracy of AgriDSS outputs (Schöning & Richter, 2021; Singh, 2018).

Second, *output review* represents the strategy where the agricultural workers are presented with a single or collection of outputs for review. Through this strategy, agricultural workers can evaluate the appropriateness of the AgriDSS outputs (predictions or recommendations) based on their experiential learning. Workers often indulge in inductive reasoning and critical thinking to form abstract concepts and informal theories that help them make quick and accurate decisions by analyzing different contexts (real-time context with the historical context) and anomalies in the data (Holzinger et al., 2022). Such reasoning can allow them to review the outputs of trained AgriDSS by simply validating (or invalidating) output based on the satisfactory fulfillment of their requirements and propose appropriate corrective measures by feeding their judgments back to the model (Dadi et al., 2020). Hence, involving agricultural workers in evaluating counterintuitive AgriDSS recommendations can enhance the action capability of AgriDSS.

The third strategy involves the participation of agricultural workers in the *inspection of the trained AgriDSS model*. The assessment of model quality is not limited to prediction accuracy and incorporates other metrics, such as coverage, confidence, task performance, and can be affected by mislabelled data, feature deficiencies, and insufficient data (Amershi et al., 2014). A *model inspection strategy* will thus allow agricultural workers to identify such errors to facilitate debugging and improve model quality. Agricultural workers can contribute as human annotators in this strategy and use their learning from active experimentation in the fields to improve AgriDSS learning by testing and validating the model and scoring the outputs (Holzinger et al., 2022; Schöning & Richter, 2021). Similarly, the concrete experiences of agricultural workers can help them identify the reasons behind the ineffective deployment and performance of AgriDSS models in real settings (Dadi et al., 2021). In agricultural applications, the transfer of the model into practical use may be considerably more complicated, and model inspection strategy provides the opportunity to recognize that models are often applied in ways that cannot be predicted at design time. Farmers and other agricultural workers can provide feedback in the form of region-specific and farm-specific data or explanations for deployment inconsistencies which, when shared through a common interface, can help developers to retrain models to be more situation-aware (Holzinger et al., 2022).

5.2 Conjoint Experiential Learning Promotes Sustainable Agriculture Outcomes

By augmenting AI capabilities, CEL should help address system, deployment, social, and ethical roadblocks to AgriDSS use. The CEL framework encourages agricultural workers' participation in AgriDSS development, which can enhance their awareness and knowledge of AI. By participating in AgriDSS development, workers can learn more about AgriDSS functionalities, understand how ML within AgriDSS operates, and become more familiar with the system (Holzinger et al., 2022; Schöning & Richter, 2021). Increased awareness and familiarity with AI systems can strengthen their trust and confidence in the AgriDSS offerings (Mohr & Kühl, 2021). Involving farmers in AgriDSS development will not only help to reduce the alienation that small farm holders feel about technology deployment and use, but it will also help them discover the potential of AgriDSS in reducing carbon emissions and making wise use of natural resources in their work. Furthermore, the CEL framework can reveal limitations in the AI model's design and user interface, allowing farmers to express concerns and provide feedback on the model and its functionalities, resulting in the development of a more user-friendly model. User-friendly systems can increase the reliability of AgriDSS and reduce privacy and security concerns. Additionally, improved AI capabilities achieved through CEL can reduce prediction biases and guide agricultural workers toward more strategic actions, supporting sustainable agricultural operations and addressing food security issues (Chandra & Collis, 2020; Cravero & Sepúlveda, 2021; FAO, 2021a). Finally, with improved AI capabilities, AgriDSS can better learn from its own experiences, which can be applied in transfer learning, multitask learning, and successful model deployment. Effective transfer learning and multitask learning can reduce data requirements, making the AgriDSS development process less carbon intensive (Vinuesa et al., 2020). In these ways, the CEL framework should help to reduce social, ethical, systems, and deployment barriers and promote the development of robust AgriDSS that support sustainable agriculture outcomes related to food security, climate change, resource conservation, and biodiversity preservation.

6 Future Research Directions for the IS Discipline

The previous section outlined how the CEL framework can enhance AgriDSS performance. It is anticipated that the interaction between technology and people will have far-reaching effects on the evolution of AgriDSS design and the relationship between technology and people over time. This section explores some of these aspects and suggests future research directions for the IS discipline (see Table 3).

First, the CEL framework depicts scenarios where agricultural workers and AI tools collaborate to multiply and combine their complementary strengths. Successful human-AI collaboration has been suggested to augment AI and human capabilities for task efficiency and performance enhancement (Grønsund & Aanestad, 2020). Continuous human-AI interaction suggests a constant transformation of human knowledge (Grønsund & Aanestad, 2020; Tarafdar et al., 2022). This transformation, however, is contingent on individuals' willingness to transform their knowledge based on AI output. As a result, the level of human engagement embedded in conjoint learning will be critical in determining the outcomes of human-AI collaboration. In terms of learning and knowledge, active engagement scenarios, in which individuals constantly integrate AI claims with their own experiences and knowledge, maybe more productive and beneficial than passive engagement, which adds no value to AI capability augmentation and knowledge building. We argue that experiential learning can help improve AgriDSS, and the constant interaction may lead to the transformation and evolution of individuals' theories and concepts and start a cycle of continuous learning and adaptation over time. While long-term exposure and interaction with AgriDSS models can be beneficial, learning acquired in a short period may raise concerns about the quality of model improvement, especially if implemented by passively engaged individuals. Short-term exposure may not be sufficient to develop knowledge that would permit the users to question AI output. Passive users in such situations may ignore or blindly accept the AI output, with no additional benefit to model improvement. Additionally, longer exposure and interaction with ML may lead to human fatigue, adversely impacting the AgriDSS model. These concerns with respect to invoking and maintaining the quality of active engagement provide many future research avenues for the management and evolution of constructive human-AI collaboration.

Second, the framework posits that exchanging knowledge between humans and machines is the crux of creating robust AI models that respond to the agricultural sector's changing requirements. In addition to the quality of human engagement, the appropriate delegation of decision authority between humans and AI is crucial to building robust AgriDSS (Fügener et al., 2022). Each agricultural field varies in environmental parameters, and individuals working in these fields may acquire varying levels of experience and knowledge. While some may have high-level analytical capabilities, allowing them to develop rich knowledge, others may lack these qualities and in-depth knowledge development (Abbasi et al., 2022). Variations in learning and knowledge acquisition create more complexities in work environments, such as agriculture that are subject to unexpected changes in working conditions. As a result, future research investigating how the delegation of decision authority will change under these situations is encouraged. As AI models increase their situation awareness and sensitivity to sudden changes in both natural and agricultural business environments, the shift in decision-making authority between humans and AI suggests an intriguing direction for future research. IS research could investigate the delegation of decision authority when there is an imbalance in knowledge transfer, such as when ML models receive inputs from less competent individuals or when the ML model deals with knowledgeable individuals who lack the competency to understand ML functionalities.

The third research direction relates to the design of CEL-supported AgriDSS that simulate the interaction between humans and AI. The framework proposes an interactive workflow between AI and human systems where the individuals and the target model influence each other's behavior and co-adaptation based on the individual’s feedback in response to the model. This suggests that the appropriate design of such interactive systems with a proper interface is critical to initiate productive dialogue between individuals and machines. However, the successful design of such interactive systems requires careful consideration of nuances that may arise at several levels. First, the design must allow the systems to communicate easily on the part of humans. Humans learn differently than AI, and some knowledge is difficult for humans to share (Fügener et al., 2022), which may lead to inconsistencies in data labeling and feedback to the AI model. For example, the user may label image data representing a specific crop, but the fact that the user did not label certain images from the same data sample does not necessarily imply that those images are non-representative. Likewise, the AI outputs should be presented in a way that is understandable and interpretable by individuals to reduce the uncertainty when relating user input and user intent (Dudley & Kristensson, 2018). Interacting with a model is unlike interacting with a conventional information structure through a user interface. The ML model evolves in response to user input, but not necessarily in a way perceived as intuitive or predictable by the individuals using it. Additionally, although CEL-supported AgriDSS have much potential as they can be used in different working environments, they pose issues in terms of branching, that is, forking events. Forking can introduce excessive overhead and duplicated development efforts in the network and can result in potential security attacks (Jameel et al., 2020). In this regard, collaborative efforts on the part of developers are required to develop systems that classify the standard from the local repository. Thus, designing an interactive interface that promotes easy dialogue between humans and machines and optimizes forking is an appropriate direction for future IS research.

Following the CEL framework, it should be possible to achieve more context-specific recommendations customized to agricultural workers' needs. CEL strategies aim to link humans to the ML model development loop in a specific way so that the machine can gain value from human knowledge and experience. Most current strategies achieve this goal through human data annotation, where the ML model in development continuously receives new annotations to be used in training (Schöning & Richter, 2021). Although this strategy may seem appropriate in theory, it can be costly and time-consuming in practice (Amershi et al., 2014). As evidenced by the literature, the agricultural sector is turning to customized and tailored AgriDSS, which are simultaneously affordable and user-friendly (Abioye et al., 2022). The main challenge is to achieve good personalization with the lowest cost in the complex mass personalization paradigm. This challenge extends beyond the improved performance of AgriDSS to the economic benefits of agricultural workers. Due to frequent changes in the agricultural working environment, workers' changing preferences are prone to impact personalization efforts adversely. Thus, striking a balance between the degree of personalization and the invested resources is critical. Additionally, changing conditions and preferences necessitate collecting both internal (user needs) and external (environmental) data leading to data privacy concerns. Given these concerns, considering the economic and ethical aspects of mass personalization are important and practical research directions.

The fifth research direction relates to the need for social and culturally representative AI solutions for small holder and marginalized agricultural communities. Despite producing 45% of the world's food (Heldreth et al., 2021), marginalized agricultural communities are not well represented in technological development. Due to the abundance of proprietary data, AI solutions target large, well-resourced farms. However, well-resourced farms' principal focus on productivity can lead to environmentally unsustainable large-scale monoculture, threatening smallholder farm survival. Additionally, the information provided by existing AI solutions is often too technical and does not correspond to how smallholder farmers think about and discuss farm operations (Heldreth et al., 2021). Current AI solutions are data-driven (satellite images, sensors) and do not account for the social, cultural, and spiritual practices of agricultural workers, some of which are key to managing the agricultural ecosystems in the face of changing social and environmental conditions (Galaz et al., 2021; Metta et al., 2022). Additional obstacles are posed due to linguistic diversity, which makes shared information unreliable. Apart from improved agricultural operations, one of the potential benefits of CEL could be in developing a platform where agricultural workers could showcase their premium products, for example, heirloom products, and share their stories. Such platforms can provide farmers with economic opportunities and make consumers more aware of farming processes. Again, the imminent challenge for the developers in this regard would be to overcome linguistic diversity and consolidate worldwide products on a single platform. In some cases, farmers tend to avoid implementing digital technologies that could detach them from plants (or animals), land, culture, and traditions (Atwal et al., 2021). In this regard, AI systems must be developed to consider social and cultural norms to ensure that the recommendations they provide are acceptable and actionable. Our proposed CEL framework provides a foundation for incorporating agricultural workers' field experiences into AI models. Nevertheless, social norms and cultural values necessitate a more systemic research approach. We encourage IS researchers to investigate the application of CEL to the development of culture conscious AI (Table 3).

Table 3. Future Research Directions

Research topic	Future research opportunities and illustrative research questions
Active human-AI collaboration and quality of engagement	• How to encourage active user engagement and maintain the quality of active engagement? • How to avoid inconsistencies in inputs and the resulting bias in the model when the individuals are prone to changing their concepts regularly? • How can active engagement be maintained in higher-dimension data labeling that requires more time and cognitive effort? • How to avoid fatigue and stagnation in agricultural workers when exposed for long periods to AI?
Authority and decision-making agency	• How can the ML model communicate and foster a clear dialogue while working with individuals with varying levels of acquired knowledge and experience? • How to develop an appropriate framework for making and adjusting decisions in a work environment prone to constant changes?
Design of CEL-supported AgriDSS model	• How to design an interactive interface that promotes easy dialogue between agricultural workers and AI? • How to carefully extract user intent from user actions? • How to reduce the uncertainty in the relationship between user intent and user input? • How to optimize forking in the CEL-supported AgriDSS?
Mass personalization of CEL-supported AgriDSS	• How to achieve the highest mass personalization with the lowest cost? • How to achieve the highest customer satisfaction through mass personalization of CEL-supported AgriDSS? • How to achieve a balance between the level of personalization (customers' needs) and effort (providers' constraints)? • What role do ethics play in mass personalization?
Culture conscious AI	• How to design AgriDSS that ensure equality, fairness, and inclusiveness? • What are the methods and criteria to verify that AgriDSS complies with general values? • How can social norms or values be adapted to newly established AI-driven agricultural practices? • How can natural language processing include multiple languages and provide a real-time translation?

7 Conclusion

AgriDSS provide immense potential to increase food security by encouraging sustainable farming activities, conserving the soil and water, and reducing the carbon footprint. Our literature review reveals that the effective use of AgriDSS is hindered at social, systems, deployment, and ethical levels. While the literature throws some conceptual light on combating these issues by proposing human and AI complementarity in the development and deployment of AgriDSS, how this complementarity can be weaved conceptually and empirically into AgriDSS design and development has not previously been addressed. The CEL framework and the research agenda suggest that combining AI learning and human experiential learning will enhance the realized benefits of AgriDSS. Moreover, conjoint experiential learning can serve the dual purpose of augmenting AI capabilities and enriching human experiential learning. Together, these purposes can help address the existing roadblocks to AgriDSS use and realize sustainable agriculture outcomes.

From a theoretical perspective, a major contribution of this study is that it investigates the use of AI in a less-explored context of agriculture. It provides a thematic classification of the current literature through a broad scoping review and systematically identifies and defines important theoretical concepts based on the literature. This study can serve as a guide for those interested in conducting research in this area. A second major contribution of this work is introducing a novel theoretical concept of CEL that can be used to understand and examine the complex interplay between technology, human abilities, and environmental factors. This framework focuses on enhancing the complementary strengths of humans in terms of leadership, creativity, and technological skills and the speed, capabilities, and performance of AI systems. As one-third of agriculture is under smallholder farmers, the CEL framework shows a path toward integrating cultural and social norms in AI development and achieving SDGs. We encourage IS researchers to explore the validity of this framework by conducting empirical research in different contexts. The third contribution of this work is the research agenda, which proposes comprehensive and novel directions for future research in AI for sustainable agriculture. The proposed future research towards mass personalization of CEL-supported AI, design of interactive AI systems, and culture conscious AI is novel, as there has been little discussion on how AI can absorb tacit user knowledge and become more culturally aware and useful. The agricultural sector is an important area of IS research in line with calls for addressing the grand societal challenges and attaining the second sustainable development goal (SDG-2). The urgency to tackle food security and environmental impacts brings more technological innovations in agriculture (Aubert et al., 2012). We support these efforts by presenting research opportunities for IS researchers to investigate agriculture worker and AI collaboration and develop holistic solutions for sustainable agriculture. From a practical standpoint, this research reinforces the importance of effective human-AI collaboration in enhancing artifact design and performance, contributing useful insights into user-centered IS design and development. This work proposes that system developers consider farmer and agriculture workers' experience in the design of AgriDSS to help reshape and redefine artifacts according to user expectations and requirements. Policymakers can consider the economic implications of AgriDSS designs at multiple levels, as the outputs of an AI tool have implications for farmers' crop selection, which in turn affects resource consumption (different crops have varying requirements) and the financial benefits realized by farmers.

As with any research, this work has certain limitations. The scoping literature review explicitly targeted AgriDSS for plant-based sustainable agriculture and did not use specific AI learning models as keywords, such as ML and deep learning. Hence this review might have missed articles that discuss these specific techniques in agricultural practices and for agricultural sustainability generally or in animal-based farming contexts. While we acknowledge this limitation, we believe the sample of literature reviewed provided a sufficient base to help inform our theorizing and the development of the research agenda. We do not intend to suggest that the research agenda covers all possible directions for research; it is merely a starting point. The value of the agenda will be tested as IS researchers use it to guide their efforts and identify additional questions and challenges that require IS research expertise and insights.

As we have presented in this paper, conjoint learning efforts can augment AI capabilities and address the limitations of AgriDSS use related to social, ethical, technical, and environmental concerns. Conjoint experiential learning can add human insights into AI development and enhance human knowledge about AI systems, leading to the exploitation of the complete potential of AgriDSS. Using this novel perspective for examining AI design and implementation in agriculture can open new avenues for future IS research and pave the way for effective AgriDSS for sustainable agriculture in practice.

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Appendix A: Overview of the Findings of the Literature Review on AgriDSS in Sustainable Agriculture

Table A1. Results for AI Resources

AI techniques	
Agent-based model	Abbasi et al. (2022), Dorin et al. (2022), FAO (2018), Fikar (2018), Jagatheesaperumal et al. (2021), Nguyen et al. (2011), Sharma et al. (2021)
Artificial Neural Network	Abbasi et al. (2022), Alexandrova et al. (2021), Bahn et al. (2021), Banjeree (2020), Basso and Antle (2020), Bhagat et al. (2022), Brownlee et al. (2018), Camarena (2020), Concepcion et al. (2021), Cowls et al. (2021), Dadi et al. (2021), Dhanya et al. (2022), Elbehri and Chestnov (2021), Ferrari et al. (2022), Galaz et al. (2021), Hungilo et al. (2019), Ingram and Maye (2020), Niforos (2020), Javaid et al. (2022), Kamyshova et al. (2022), Klerkx and Rose (2020), Liakos et al. (2018), Liu et al. (2022), Magalhães et al. (2022), Marvin et al. (2022), Mohr and Kühl (2021), Newlands et al. (2019), Nyéki et al. (2021), Ogawa et al. (2021), Ridwan et al. (2021), Santos Valle and Kienzle (2020), Schöning and Richter (2021), Sharma (2021), Spanaki et al. (2022b), Suh et al. (2018), Trabelsi et al. (2022), Vinuesa et al. (2020), Zhang et al. (2022)
Artificial Intelligence	Atwal et al. (2021), Bahn et al. (2021), Basso and Antle (2020), Bestelmeyer et al. (2020), Bonaccorsi et al. (2017), Chamara et al. (2020), Chandra and Collis (2021), Cowls et al. (2021), Dadi et al. (2021), Dara et al. (2022), Dayioglu and Turker (2022), Elbehri and Chestnov (2021), FAO (2020), FAO (2018), FAO (2020), FAO (2021a), Feng et al. (2019), Fikar (2018), Galaz et al. (2021), García Pereira et al. (2020), Gerhards et al. (2022), Gonzalez-de-Santos et al. (2020), Guillén-Navarro et al. (2020) Heldreth et al. (2021), Henkhaus et al. (2020), Holzinger et al. (2022), Hungilo et al. (2019), Niforos (2020), Javaid et al. (2022), Jung et al. (2021), Kalyanaraman et al. (2022), Klerkx and Rose (2020), Kugler (2022), Lezoche et al. (2020), Linaza et al. (2021), Liu et al. (2020), MacPherson et al. (2022), Martelli et al. (2020), Marvin et al. (2022), Metta et al. (2022), Mohr and Kühl (2021), Ogawa et al. (2021), Roshanianfard et al. (2020), Ryan (2022), Saheb et al. (2022), Schoormann et al. (2021), Sharma (2021), Siregar et al. (2022), Spanaki et al. (2022a), Spanaki et al. (2022b), Sparrow et al. (2021), Vinuesa et al. (2020), Zhang et al. (2022)
Computer Vision	Araújo et al. (2021), Chandra and Collis (2021), Concepcion et al. (2021), Cowls et al. (2021), Dhanya et al. (2022), Dorin et al. (2022), Feng et al. (2019), Ferrari et al. (2022), Guru and Mallikarjuna (2010), Hungilo et al. (2019), Kamyshova et al. (2022), Kelly et al. 2022
Decision Tree	Araújo et al. (2021), Bonaccorsi et al. (2017), Klerkx and Rose (2020), Newlands et al. (2019), Ridwan et al. (2021)
Deep Learning	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Benos et al. (2021), Bhat and Huang (2021), Chamara et al. (2020), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dhanya et al. (2022), Elavarasan and Vincent (2020), Elbehri and Chestnov (2021), Fenu and Malloci (2022), Fiehn et al. (2018), Galaz et al. (2021), García Pereira et al. (2020), Garske et al. (2021), Guillén-Navarro et al. (2020), Holzinger et al. (2022), Niforos (2020), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Jung et al. (2021), Khan et al. (2022), Kugler (2022), Kumar et al. (2020), Linaza et al. (2021), Liu et al. (2022), Masi et al. (2021), Newlands et al. (2019), Ofori and El-Gayar (2020), Panchbhaiyye and Ogunfunmi (2018), Rao et al. (2021), Saggi and Jain (2022), Saheb et al. (2022), Saiz-Rubio and Rovira-Más (2020), Schoormann et al. (2021), Sharma (2021), Siregar et al. (2022), Song et al. (2016), Spanaki et al. (2022b), Suh et al. (2018), Van Klompenburg et al. (2020), Wang et al. (2022)
Digital twin	Galaz et al. (2021), Gonzalez-de-Santos et al. (2020), Kugler (2022), Linaza et al. (2021), Marvin et al. (2022), Zhang et al. (2022)
Expert Systems	Bhat and Huang (2021), Chamara et al. (2020), Hungilo et al. (2019), Lezoche et al. (2020), Liu et al. (2020), Schöning and Richter (2021), Sharma (2021), Sharma et al. (2021)
Fuzzy Logic	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Benos et al. (2021), Bhagat et al. (2022), Bhat and Huang (2021), Chamara et al. (2020), Concepcion et al. (2021), Escamilla-García et al. (2020), Feng et al. (2019), Giusti and Marsili-Libelli (2015), Niforos (2020), Jagatheesaperumal et al. (2021), Kamyshova et al. (2022), Kour and Arora (2020), Lezoche et al. (2020), Magalhães et al. (2022), Mugiyo et al. (2021), Roshanianfard et al. (2020), Saggi and Jain (2022), Saheb et al. (2022), Saiz-Rubio and Rovira-Más (2020), Sharma (2021), Sharma et al. (2021), Siregar et al. (2022), Spanaki et al. (2022b), Viani et al. (2017)

Genetic Algorithm	Arkeman et al. (2021), Brownlee et al. (2018), Chamara et al. (2020), Concepcion et al. (2021), Elavarasan and Vincent (2020), Escamilla-García et al. (2020), Guru and Mallikarjuna (2010), Lezoche et al. (2020), Roshanianfard et al. (2020), Saggi and Jain (2022), Saheb et al. (2022), Sharma et al. (2021), Siregar et al. (2022), Spanaki et al. (2022b)
Machine Learning	Abbasi et al. (2022), Abioye et al. (2022), Alexandrova et al. (2021), Araújo et al. (2021), Arkeman et al. (2021), Banjeree (2020), Benos et al. (2021), Bhagat et al. (2022), Bhat and Huang (2021), Brownlee et al. (2018), Camarena (2020), Chandra and Collis (2021), Concepcion et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dadi et al. (2021), Dhanya et al. (2022), Elavarasan and Vincent (2020), Escamilla-García et al. (2020) Everingham et al. (2016), Fenu and Malloci (2019), Fenu and Malloci (2022), Fiehn et al. (2018), Gandhi et al. (2016), Garske et al. (2021), Giusti and Marsili-Libelli (2015), Henkhaus et al. (2020), Hussain et al. (2021), Ingram and Maye (2020), Niforos (2020), Jagatheesaperumal et al. (2021), Kamyshova et al. (2022), Khan et al. (2022), Kim et al. (2020), Kour and Arora (2020), Kugler (2022), Kumar et al. (2020), Liakos et al. (2018), Liu et al. (2022), López-Correa et al. (2022), Magalhães et al. (2022), Martelli et al. (2020), Masi et al. (2021), Mugiyo et al. (2021), Newlands et al. (2019), Nyéki et al. (2021), Ofori and El-Gayar (2020), Basso and Antle (2020), Panchbhaiyye and Ogunfunmi (2018), Park et al. (2018), Raju et al. (2006), Rao et al. (2021), Ridwan et al. (2021), Saggi and Jain (2022), Saiz-Rubio and Rovira-Más (2020), Shankar et al. (2020), Sharma (2021), Sharma et al. (2021), Singh (2018), Siregar et al. (2022), Song et al. (2016), Suh et al. (2018), Trabelsi et al. (2022), Trendov et al. (2020), Van Klompenburg et al. (2020), Viani et al. (2017), Wang et al. (2022)
Random Forest	Abioye et al. (2022), Alexandrova et al. (2021), Araújo et al. (2021), Benos et al. (2021), Chamara et al. (2020), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dhanya et al. (2022), Everingham et al. (2016), García Pereira et al. (2020), Hungilo et al. (2019), Hussain et al. (2021), Jagatheesaperumal et al. (2021), Khan et al. (2022), Liakos et al. (2018), Linaza et al. (2021), Martelli et al. (2020), Newlands et al. (2019), Nyéki et al. (2021), Ridwan et al. (2021), Saggi and Jain (2022), Shankar et al. (2020), Trabelsi et al. (2022), Van Klompenburg et al. (2020)
Reinforcement Learning	Araújo et al. (2021), Dara et al. (2022), García Pereira et al. (2020)
Robot	Araújo et al. (2021), Chamara et al. (2020), Dadi et al. (2021), Ferrari et al. (2022), Gonzalez-de-Santos et al. (2020), Liu et al. (2020), Marinoudi et al. (2019), Roshanianfard et al. (2020), Santos Valle and Kienzle (2020), Sharma et al. (2021), Spanaki et al. (2022b), Wang et al. (2022)
Support Vector Machine	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Benos et al. (2021), Bhagat et al. (2022), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dhanya et al. (2022), Escamilla-García et al. (2020), Fenu and Malloci (2019), Gandhi et al. (2016), Holzinger et al. (2022), Hungilo et al. (2019), Hussain et al. (2021), Jagatheesaperumal et al. (2021), Khan et al. (2022), Liakos et al. (2018), Nyéki et al. (2021), Ridwan et al. (2021), Saggi and Jain (2022), Schoormann et al. (2021), Spanaki et al. (2022b), Suh et al. (2018), Trabelsi et al. (2022), Van Klompenburg et al. (2020)
Unmanned Aerial Vehicle	Abbasi et al. (2022), Araújo et al. (2021), Benos et al. (2021), Bhagat et al. (2022), Bhat and Huang (2021), Chamara et al. (2020), Dayioglu and Turker (2022), Dhanya et al. (2022), Elbehri and Chestnov (2021), Gerhards et al. (2022), Gonzalez-de-Santos et al. (2020), Holzinger et al. (2022), Hussain et al. (2021), Javaid et al. (2022), Jung et al. (2021), Kour and Arora (2020), Liakos et al. (2018), MacPherson et al. (2022), Rao et al. (2021), Saiz-Rubio and Rovira-Más (2020), Spanaki et al. (2022a), Spanaki et al. (2022b), Suh et al. (2018), Trendov et al. (2020), Wang et al. (2022), Zhang et al. (2022)
AI design and development phase	

Conceptual	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Arkeman et al. (2021), Bahn et al. (2021), Banjeree (2020), Basso and Antle (2020), Benos et al. (2021), Bestelmeyer et al. (2020), Bhagat et al. (2022) Bhat and Huang (2021), Camarena (2020), Chamara et al. (2020), Chandra and Collis (2021), Concepcion et al. (2021), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022), Dayioglu and Turker (2022), Dhanya et al. (2022), Escamilla-García et al. (2020), FAO (2018), FAO (2021a), Ferrari et al. (2022), Galaz et al. (2021), Garske et al. (2021), Gerhards et al. (2022), Gonzalez-de-Santos et al. (2020), Heldreth et al. (2021), Henkhaus et al. (2020), Holzinger et al. (2022), Hungilo et al. (2019), Hussain et al. (2021), Ingram and Maye (2020), Niforos (2020), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Kalyanaraman et al. (2022), Kelly et al. (2022), Klerkx and Rose (2020), Kour and Arora (2020), Kugler (2022), Kumar et al. (2020), Lezoche et al. (2020), Liakos et al. (2018), Linaza et al. (2021), Liu et al. (2022), MacPherson et al. (2022), Martelli et al. (2020), Marvin et al. (2022), Masi et al. (2021), Metta et al. (2022), Mugiyo et al. (2021), Raju et al. (2006), Saggi and Jain (2022), Rao et al. (2021), Ryan (2022), Saheb et al. (2022), Saiz-Rubio and Rovira-Más (2020), Santos Valle and Kienzle (2020), Shankar et al. (2020), Sharma (2021), Sharma et al. (2021), Siregar et al. (2022), Spanaki et al. (2022b), Sparrow et al. (2021), Suh et al. (2018), Trendov et al. (2020), Van Klompenburg et al. (2020), Vinuesa et al. (2020), Wang et al. (2022), Zhang et al. (2022)
Prototype	Atwal et al. (2021), Bonaccorsi et al. (2017), Brownlee et al. (2018), Elavarasan and Vincent (2020), Everingham et al. (2016), FAO (2020), Feng et al. (2019), Fenu and Malloci (2019), Fiehn et al. (2018), Fikar (2018), Gandhi et al. (2016), García Pereira et al. (2020), Giusti and Marsili-Libelli (2015), Guillén-Navarro et al. (2020), Guru and Mallikarjuna (2010), Kamyshova et al. (2022), Khan et al. (2022), Liu et al. (2020), López-Correa et al. (2022), Marinoudi et al. (2019), Newlands et al. (2019), Nguyen et al. (2011), Nyéki et al. (2021), Ofori and El-Gayar (2020), Ogawa et al. (2021), Basso and Antle (2020), Panchbhaiyye and Ogunfunmi (2018), Park et al. (2018), Schöning and Richter (2021), Schoormann et al. (2021), Singh (2018), Spanaki et al. (2022a), Trabelsi et al. (2022), Viani et al. (2017)
Deployed	Alexandrova et al. (2021), FAO (2018), FAO (2020), Fenu and Malloci (2019), Khan et al. (2022), Magalhães et al. (2022), Singh (2018), Song et al. (2016)

Table A2. Results for AgriDSS Capabilities

Situation awareness	Abbasi et al. (2022), Abioye et al. (2022), Alexandrova et al. (2021), Araújo et al. (2021), Benos et al. (2021), Bhat and Huang (2021), Chamara et al. (2020), Chandra and Collis (2021), Concepcion et al. (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022), Dhanya et al. (2022), Escamilla-García et al. (2020) Feng et al. (2019), Fenu and Malloci (2019), Fiehn et al. (2018), Fikar (2018), Garske et al. (2021), Gonzalez-de-Santos et al. (2020), Guillén-Navarro et al. (2020), Ingram and Maye (2020), Jagatheesaperumal et al. (2021), Jung et al. (2021), Kalyanaraman et al. (2022), Kelly et al. (2022), Kim et al. (2020), Kour and Arora (2020), Khan et al. (2022), Lezoche et al. (2020), Liakos et al. (2018), Linaza et al. (2021), Liu et al. (2020), Liu et al. (2022), López-Correa et al. (2022), MacPherson et al. (2022), Magalhães et al. (2022), Marinoudi et al. (2019), Masi et al. (2021), Mugiyo et al. (2021), Ofori and Gayar (2020), Ogawa et al. (2021), Raju et al. (2006), Saggi and Jain (2022), Rao et al. (2021), Saiz-Rubio and Rovira-Más (2020), Schöning and Richter (2021), Sharma (2021), Spanaki et al. (2022b), Suh et al. (2018), Trendov et al. (2020), Viani et al. (2017), Wang et al. (2022), Zhang et al. (2022)

Pattern recognition	Abbasi et al. (2022), Abioye et al. (2022), Alexandrova et al. (2021), Araújo et al. (2021), Arkeman et al. (2021), Bahn et al. (2021), Benos et al. (2021), Bestelmeyer et al. (2020), Bhat and Huang (2021), Brownlee et al. (2018), Camarena (2020), Chamara et al. (2020), Chandra and Collis (2021), Concepcion et al. (2021), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022), Dhanya et al. (2022), Elavarasan and Vincent (2020), Elbehri and Chestnov (2021), Escamilla-García et al. (2020), Everingham et al. (2016), FAO (2018), FAO (2020), Feng et al. (2019), Fenu and Malloci (2019), Fenu and Malloci (2022), Ferrari et al. (2022), Gandhi et al. (2016), Fiehn et al. (2018), Fikar (2018), García Pereira et al. (2020), Garske et al. (2021), Gerhards et al. (2022), Giusti and Marsili-Libelli (2015), Gonzalez-de-Santos et al. (2020), Guillén-Navarro et al. (2020), Guru and Mallikarjuna (2010), Henkhaus et al. (2020), Holzinger et al. (2022), Hungilo et al. (2019), Hussain et al. (2021), Ingram and Maye (2020), Jagatheesaperumal et al. (2021), Jung et al. (2021), Kalyanaraman et al. (2022), Kamyshova et al. (2022), Khan et al. (2022), Kim et al. (2020), Kour and Arora (2020), Kumar et al. (2020), Lezoche et al. (2020), Liakos et al. (2018), Linaza et al. (2021), Liu et al. (2020), Liu et al. (2022) López-Correa et al. (2022), MacPherson et al. (2022), Magalhães et al. (2022), Marinoudi et al. (2019), Martelli et al. (2020), Masi et al. (2021), Mohr and Kühl (2021), Mugiyo et al. (2021), Newlands et al. (2019), Nguyen et al. (2011), Nyéki et al. (2021) Ofori and Gayar (2020), Ogawa et al. (2021), Orn et al. (2018), Panchbhaiyye and Ogunfunmi (2018), Park et al. (2018), Raju et al. (2006), Rao et al. (2021), Ridwan et al. (2021), Ryan (2022), Saggi and Jain (2022), Saheb et al. (2022), Saiz-Rubio and Rovira-Más (2020), Schöning and Richter (2021), Schoormann et al. (2021), Shankar et al. (2020), Sharma (2021), Sharma et al. (2021), Singh (2018), Siregar et al. (2022), Spanaki et al. (2022a), Spanaki et al. (2022b), Sparrow et al. (2021), Suh et al. (2018), Trabelsi et al. (2022), Trendov et al. (2020), Van Klompenburg et al. (2020), Viani et al. (2017), Wang et al. (2022), Zhang et al. (2022)
Action	Abbasi et al. (2022), Abioye et al. (2022), Alexandrova et al. (2021), Araújo et al. (2021), Arkeman et al. (2021), Bahn et al. (2021), Benos et al. (2021), Bestelmeyer et al. (2020), Bhagat et al. (2022), Bhat and Huang (2021), Brownlee et al. (2018), Camarena (2020), Chamara et al. (2020), Chandra and Collis (2021), Concepcion et al. (2021), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022) Dhanya et al. (2022), Elavarasan and Vincent (2020), Elbehri and Chestnov (2021), Escamilla-García et al. (2020), Everingham et al. (2016), FAO (2018), FAO (2020), FAO (2021b), Feng et al. (2019), Fenu and Malloci (2019), Fenu and Malloci (2022), Ferrari et al. (2022), Fiehn et al. (2018), Fikar (2018), Gandhi et al. (2016), García Pereira et al. (2020) Garske et al. (2021), Gerhards et al. (2022) Giusti and Marsili-Libelli (2015), Gonzalez-de-Santos et al. (2020) Guillén-Navarro et al. (2020) Guru and Mallikarjuna (2010), Henkhaus et al. (2020), Holzinger et al. (2022), Hungilo et al. (2019), Hussain et al. (2021), Ingram and Maye (2020), Niforos (2020), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Jung et al. (2021), Kalyanaraman et al. (2022), Kamyshova et al. (2022), Khan et al. (2022), Kim et al. (2020), Kour and Arora (2020), Kumar et al. (2020), Lezoche et al. (2020), Liakos et al. (2018), Linaza et al. (2021), Liu et al. (2020), Liu et al. (2022), López-Correa et al. (2022), MacPherson et al. (2022), Magalhães et al. (2022), Marinoudi et al. (2019), Martelli et al. (2020), Marvin et al. (2022), Masi et al. (2021), Mohr and Kühl (2021), Mugiyo et al. (2021), Newlands et al. (2019), Nguyen et al. (2011), Ofori and Gayar (2020), Ogawa et al. (2021), Orn et al. (2018), Panchbhaiyye and Ogunfunmi (2018), Park et al. (2018), Raju et al. (2006), Rao et al. (2021), Ridwan et al. (2021), Ryan (2022), Saggi and Jain (2022), Saheb et al. (2022), Saiz-Rubio and Rovira-Más (2020), Schöning and Richter (2021), Shankar et al. (2020), Sharma (2021), Sharma et al. (2021), Schoormann et al. (2021), Singh (2018), Siregar et al. (2022), Spanaki et al. (2022a), Spanaki et al. (2022b), Sparrow et al. (2021), Suh et al. (2018), Trabelsi et al. (2022), Trendov et al. (2020), Van Klompenburget al. (2020), Viani et al. (2017), Wang et al. (2022), Zhang et al. (2022)

Learn	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Arkeman et al. (2021), Benos et al. (2021), Bestelmeyer et al. (2020), Bhagat et al. (2022), Bhat and Huang (2021), Brownlee et al. (2018), Camarena (2020), Chamara et al. (2020), Chandra and Collis (2021), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022), Dhanya et al. (2022), Elavarasan and Vincent (2020), Escamilla-García et al. (2020), Everingham et al. (2016), FAO (2021b), Feng et al. (2019) Fenu and Malloci (2019), Fiehn et al. (2018), Fikar (2018), Gandhi et al. (2016), García Pereira et al. (2020), Garske et al. (2021), Gerhards et al. (2022), Giusti and Marsili-Libelli (2015), Guillén-Navarro et al. (2020), Guru and Mallikarjuna (2010), Henkhaus et al. (2020), Holzinger et al. (2022), Hungilo et al. (2019), Ingram and Maye (2020), Jagatheesaperumal et al. (2021), Kalyanaraman et al. (2022), Kamyshova et al. (2022), Kelly et al. (2022), Khan et al. (2022), Kim et al. (2020), Kour and Arora (2020), Kumar et al. (2020), Lezoche et al. (2020), Liakos et al. (2018), Linaza et al. (2021), Liu et al. (2022), López-Correa et al. (2022), MacPherson et al. (2022), Magalhães et al. (2022), Mohr and Kühl (2021), Nguyen et al. (2011), Nyéki et al. (2021), Ofori and Gayar (2020), Orn et al. (2018), Panchbhaiyye and Ogunfunmi (2018), Park et al. (2018), Raju et al. (2006), Rao et al. (2021), Ridwan et al. (2021), Saggi and Jain (2022), Saheb et al. (2022), Saiz-Rubio and Rovira-Más (2020), Schöning and Richter (2021), Sharma (2021), Sharma et al. (2021), Schoormann et al. (2021), Singh (2018), Siregar et al. (2022), Spanaki et al. (2022b), Suh et al. (2018), Trabelsi et al. (2022), Van Klompenburg et al. (2020), Viani et al. (2017), Wang et al. (2022), Zhang et al. (2022)

Table A3. Results for Types of Agricultural Tasks

Agricultural tasks	
Agricultural efficiency	Garske et al. (2021), Klerkx and Rose (2020), MacPherson et al. (2022)
Agricultural supply chain decision making	Araújo et al. (2021), Concepcion et al. (2021), Gonzalez-de-Santos et al. (2020), Jagatheesaperumal et al. (2021), Lezoche et al. (2020), Masi et al. (2021)
Crop management	Abbasi et al. (2022), Bahn et al. (2021), Banjeree (2020), Basso and Antle (2020), Benos et al. (2021), Bestelmeyer et al. (2020), Bhagat et al. (2022), Bhat and Huang (2021), Camarena (2020), Chamara et al. (2020), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dayioglu and Turker (2022), Dorin et al. (2022), Elbehri and Chestnov (2021), Ferrari et al. (2022), Galaz et al. (2021), Niforos (2020), Javaid et al. (2022), Jung et al. (2021), Kalyanaraman et al. (2022), Kelly et al. (2022), Kim et al. (2020), Kour and Arora (2020), Kugler (2022), Liakos et al. (2018), Linaza et al. (2021), Liu et al. (2020), Marvin et al. (2022), Ogawa et al. (2021), Rao et al. (2021), Roshanianfard et al. (2020), Ryan (2022), Santos Valle and Kienzle (2020), Sharma (2021), Sharma et al. (2021), Siregar et al. (2022), Spanaki et al. (2022b), Van Klompenburg et al. (2020), Vinuesa et al. (2020), Wang et al. (2022), Zhang et al. (2022)
Crop productivity	Chandra and Collis (2021), Dara et al. (2022), Elavarasan and Vincent (2020), Everingham et al. (2016), FAO (2018), FAO (2021b), Galaz et al. (2021), Gandhi et al. (2016), Heldreth et al. (2021), Henkhaus et al. (2020), Hussain et al. (2021), Holzinger et al. (2022), MacPherson et al. (2022), Marinoudi et al. (2019), Newlands et al. (2019), Nyéki et al. (2021), Park et al. (2018), Saiz-Rubio and Rovira-Más (2020), Spanaki et al. (2022a), Sparrow et al. (2021)
Crop quality estimation	Feng et al. (2019), Fikar (2018), Guru and Mallikarjuna (2010), Kumar et al. (2020), Magalhães et al. (2022)
Disease identification and management	Araújo et al. (2021), Arkeman et al. (2021), Atwal et al. (2021), Brownlee et al. (2018), Dara et al. (2022), Dhanya et al. (2022), FAO (2018), FAO (2020), Fenu and Malloci (2019), Fenu and Malloci (2022), Hungilo et al. (2019), Liu et al. (2022), Saiz-Rubio and Rovira-Más (2020), Shankar et al. (2020), Singh (2018)
Energy use and management	Basso and Antle (2020), Bonaccorsi et al. (2017), Escamilla-García et al. (2020), Saheb et al. (2022)
Irrigation and water management	Abioye et al. (2022), Benos et al. (2021), Dara et al. (2022), Giusti and Marsili-Libelli (2015), Guillén-Navarro et al. (2020), Kamyshova et al. (2022), Martelli et al. (2020), Raju et al. (2006), Rao et al. (2021), Ridwan et al. (2021), Saggi and Jain (2022), Saiz-Rubio and Rovira-Más (2020), Sharma (2021), Siregar et al. (2022), Song et al. (2016), Trabelsi et al. (2022), Trendov et al. (2020), Viani et al. (2017)
Land use and management	Benos et al. (2021), García Pereira et al. (2020), Khan et al. (2022), Mugiyo et al. (2021), Orn et al. (2018), Sharma (2021), Siregar et al. (2022), Trendov et al. (2020)

Market price estimation	Ooge and Verbert (2022)
Pest identification and management	Arkeman et al. (2021), FAO (2018), Fiehn et al. (2018), Liu et al. (2022), Nguyen et al. (2011), Panchbhaiyye and Ogunfunmi (2018)
Risk management	Schoormann et al. (2021)
Weather prediction	Escamilla-García et al. (2020)
Weed detection and management	Araújo et al. (2021), Arkeman et al. (2021), Dara et al. (2022), Escamilla-García et al. (2020), FAO (2018), Gerhards et al. (2022), López-Correa et al. (2022), Metta et al. (2022), Ofori and Gayar (2020), Rao et al. (2021), Saiz-Rubio and Rovira-Más (2020), Suh et al. (2018)
Sustainability goals	
SDG 1	Camarena (2020), Elbehri and Chestnov (2021), Linaza et al. (2021), Metta et al. (2022), Vinuesa et al. (2020)
SDG 2	Camarena (2020), Alexandrova et al. (2021), Banjeree (2020), Bhagat et al. (2022), Chamara et al. (2020), Dayioglu and Turker (2022), Elbehri and Chestnov (2021), FAO (2020), Holzinger et al. (2022), Niforos (2020), Linaza et al. (2021), MacPherson et al. (2022), Magalhães et al. (2022), Panchbhaiyye and Ogunfunmi (2018), Masi et al. (2021), Metta et al. (2022), Santos Valle and Kienzle (2020), Schöning and Richter (2021), Schoormann et al. (2021), Spanaki et al. (2022a), Trabelsi et al. (2022), Trendov et al. (2020), Vinuesa et al. (2020)
SDG 3	Dayioglu and Turker (2022), MacPherson et al. (2022), Magalhães et al. (2022), Masi et al. (2021), Metta et al. (2022)
SDG 4	Metta et al. (2022), Vinuesa et al. (2020)
SDG 5	Vinuesa et al. (2020)
SDG 6	Alexandrova et al. (2021), Masi et al. (2021), Metta et al. (2022), Schöning and Richter (2021), Trabelsi et al. (2022), Vinuesa et al. (2020)
SDG 7	Dayioglu and Turker (2022), Niforos (2020), Masi et al. (2021), Metta et al. (2022), Saheb et al. (2022), Vinuesa et al. (2020)
SDG 8	Elbehri and Chestnov (2021), MacPherson et al. (2022), Masi et al. (2021), Metta et al. (2022), Vinuesa et al. (2020)
SDG 9	Masi et al. (2021), Metta et al. (2022)
SDG 10	Metta et al. (2022), Vinuesa et al. (2020)
SDG 11	Metta et al. (2022), Santos Valle and Kienzle (2020), Vinuesa et al. (2020)
SDG 12	Concepcion et al. (2021), Elbehri and Chestnov (2021), Holzinger et al. (2022), Linaza et al. (2021), Magalhães et al. (2022), Masi et al. (2021), Metta et al. (2022), Ofori and Gayar (2020), Ogawa et al. (2021), Spanaki et al. (2022a), Schöning and Richter (2021), Vinuesa et al. (2020)
SDG 13	Camarena (2020), Cowls et al. (2021), Dayioglu and Turker (2022), Elbehri and Chestnov (2021), Garske et al. (2021), Linaza et al. (2021), MacPherson et al. (2022), Masi et al. (2021), Metta et al. (2022), Saiz-Rubio and Rovira-Más (2020), Trendov et al. (2020), Vinuesa et al. (2020)
SDG 14	Camarena (2020), Cowls et al. (2021), Elbehri and Chestnov (2021), Metta et al. (2022), Spanaki et al. (2022a)
SDG 15	Alexandrova et al. (2021), Camarena (2020), Cowls et al. (2021), Dayioglu and Turker (2022), Elbehri and Chestnov (2021), Metta et al. (2022), Spanaki et al. (2022a), Vinuesa et al. (2020)

Sustainability	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Arkeman et al. (2021), Atwal et al. (2021), Bahn et al. (2021), Basso and Antle (2020), Benos et al. (2021), Bestelmeyer et al. (2020), Bhat and Huang (2021), Bonaccorsi et al. (2017), Brownlee et al. (2018), Camarena (2020), Chandra and Collis (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022), Dhanya et al. (2022), Dorin et al. (2022), Elavarasan and Vincent (2020), Escamilla-García et al. (2020), Everingham et al. (2016), FAO (2018), FAO (2020), FAO (2021a), Feng et al. (2019), Fenu and Malloci (2019), Fenu and Malloci (2022), Ferrari et al. (2022), Fiehn et al. (2018), Fikar (2018), Galaz et al. (2021), Gandhi et al. (2016), García Pereira et al. (2020), Gerhards et al. (2022), Giusti and Marsili-Libelli (2015), Gonzalez-de-Santos et al. (2020), Guillén-Navarro et al. (2020), Guru and Mallikarjuna (2010), Heldreth et al. (2021), Henkhaus et al. (2020), Hungilo et al. (2019), Hussain et al. (2021), Ingram and Maye (2020), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Jung et al. (2021), Kalyanaraman et al. (2022), Kamyshova et al. (2022), Kelly et al. (2022), Khan et al. (2022), Kim et al. (2020), Klerkx and Rose (2020), Kour and Arora (2020), Kugler (2022), Kumar et al. (2020), Lezoche et al. (2020), Liakos et al. (2018), Liu et al. (2020), Liu et al. (2022), López-Correa et al. (2022), Marinoudi et al. (2019), Martelli et al. (2020), Marvin et al. (2022), Mohr and Kühl (2021), Mugiyo et al. (2021), Newlands et al. (2019), Nguyen et al. (2011), Nyéki et al. (2021), Ooge and Verbert (2022), Orn et al. (2018), Park et al. (2018), Raju et al. (2006), Rao et al. (2021), Ridwan et al. (2021), Roshanianfard et al. (2020), Ryan (2022), Saggi and Jain (2022), Saiz-Rubio and Rovira-Más (2020), Shankar et al. (2020), Sharma (2021), Sharma et al. (2021), Singh (2018), Siregar et al. (2022), Spanaki et al. (2022b), Sparrow et al. (2021), Suh et al. (2018), Van Klompenburg et al. (2020), Viani et al. (2017), Wang et al. (2022), Zhang et al. (2022)

Table A4. Results for Task Augmentation

Agricultural task efficiency	
Crop management efficiency	Abbasi et al. (2022), Bahn et al. (2021), Banjeree (2020), Basso and Antle (2020), Benos et al. (2021), Bestelmeyer et al. (2020), Bhagat et al. (2022), Bhat and Huang (2021), Camarena (2020), Chamara et al. (2020), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dayioglu and Turker (2022), Dorin et al. (2022), Elbehri and Chestnov (2021), Ferrari et al. (2022), Galaz et al. (2021), Niforos (2020), Javaid et al. (2022), Jung et al. (2021), Kalyanaraman et al. (2022), Kelly et al. (2022), Kim et al. (2020), Kour and Arora (2020), Kugler (2022), Liakos et al. (2018), Linaza et al. (2021), Liu et al. (2020), Marvin et al. (2022), Ogawa et al. (2021), Rao et al. (2021), Roshanianfard et al. (2020), Ryan (2022), Santos Valle and Kienzle (2020), Sharma (2021), Sharma et al. (2021), Siregar et al. (2022), Spanaki et al. (2022b), Van Klompenburg et al. (2020), Vinuesa et al. (2020), Wang et al. (2022), Zhang et al. (2022)
Crop resilience	Henkhaus et al. (2020), Jung et al. (2021)
Climate change mitigation	Dhanya et al. (2022), Elavarasan and Vincent (2020), FAO (2018), García Pereira et al. (2020), Ogawa et al. (2021), Schöning and Richter (2021), Siregar et al. (2022), Spanaki et al. (2022a)
Enhanced plant identification, improved plant health	Dhanya et al. (2022), Metta et al. (2022), Ofori and Gayar (2020), Shankar et al. (2020), Singh (2018), Suh et al. (2018)
Economic gain	Camarena (2020), Dorin et al. (2022), Everingham et al. (2016), Gandhi et al. (2016), Garske et al. (2021), Gonzalez-de-Santos et al. (2020), Holzinger et al. (2022), Jung et al. (2021), Linaza et al. (2021), MacPherson et al. (2022), Magalhães et al. (2022), Marinoudi et al. (2019), Newlands et al. (2019), Nyéki et al. (2021), Ooge and Verbert (2022), Van Klompenburg et al. (2020)
Improved disease prevention and control	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Atwal et al. (2021), Dara et al. (2022), Dhanya et al. (2022), FAO (2018), Fenu and Malloci (2019), Fenu and Malloci (2022), Hungilo et al. (2019), Liu et al. (2022), Saiz-Rubio and Rovira-Más (2020), Shankar et al. (2020), Sharma (2021), Singh (2018)
Improved energy management	Basso and Antle (2020), Bonaccorsi et al. (2017), Metta et al. (2022), Saheb et al. (2022)

Productivity gain	Abbasi et al. (2022), Banjeree (2020), Basso and Antle (2020), Benos et al. (2021), Bhagat et al. (2022), Bhat and Huang (2021), Brownlee et al. (2018), Camarena (2020), Chandra and Collis (2021), Dayioglu and Turker (2022), Dorin et al. (2022), Elbehri and Chestnov(2021), Everingham et al. (2016), FAO (2020), FAO (2018), FAO (2021b), Fenu and Malloci (2019), Ferrari et al. (2022), Galaz et al. (2021), Gerhards et al. (2022), Heldreth et al. (2021), Henkhaus et al. (2020), Holzinger et al. (2022), Hungilo et al. (2019), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Kamyshova et al. (2022), Kour and Arora (2020), Kumar et al. (2020), Liakos et al. (2018), Linaza et al. (2021), MacPherson et al. (2022), Marinoudi et al. (2019), Martelli et al. (2020), Metta et al. (2022), Ofori and Gayar (2020), Ogawa et al. (2021), Ryan (2022), Santos Valle and Kienzle (2020), Shankar et al. (2020) Singh (2018), Song et al. (2016), Trendov et al. (2020), Vinuesa et al. (2020)
Reduced human labor	Atwal et al. (2021), Brownlee et al. (2018), Chamara et al. (2020), Dhanya et al. (2022), Gonzalez-de-Santos et al. (2020), Kalyanaraman et al. (2022), Liu et al. (2020), Raju et al. (2006), Sharma et al. (2021), Singh (2018)
Sustainability goal efficiency	
Reduced chemical application	Brownlee et al. (2018), FAO (2018), López-Correa et al. (2022), Metta et al. (2022)
Resource efficiency and biodiversity conservation	Abbasi et al. (2022), Abioye et al. (2022), Atwal et al. (2021), Benos et al. (2021), Dhanya et al. (2022), FAO (2021b), Fikar (2018), García Pereira et al. (2020), Garske et al. (2021), Giusti and Marsili-Libelli (2015), Guillén-Navarro et al. (2020), Kalyanaraman et al. (2022), Kamyshova et al. (2022), Khan et al. (2022), Linaza et al. (2021), Martelli et al. (2020), Mugiyo et al. (2021), Orn et al. (2018), Raju et al. (2006), Ridwan et al. (2021), Saggi and Jain (2022), Sharma et al. (2021), Siregar et al. (2022), Spanaki et al. (2022a), Trabelsi et al. (2022), Trendov et al. (2020), Viani et al. (2017), Zhang et al. (2022)
Supply chain efficiency	Araújo et al. (2021), Concepcion et al. (2021), Dadi et al. (2021), Jagatheesaperumal et al. (2021), Lezoche et al. (2020), Masi et al. (2021)
Waste reduction	Bonaccorsi et al. (2017), Concepcion et al. (2021), Fikar (2018), Gerhards et al. (2022), Hungilo et al. (2019), Marvin et al. (2022), Masi et al. (2021), Panchbhaiyye and Ogunfunmi (2018), Spanaki et al. (2022a)
Environmental sustainability	Abbasi et al. (2022), Alexandrova et al. (2021), Araújo et al. (2021), Bahn et al. (2021), Banjeree (2020), Basso and Antle (2020), Benos et al. (2021), Bestelmeyer et al. (2020), Bhagat et al. (2022), Bhat and Huang (2021), Bonaccorsi et al. (2017), Brownlee et al. (2018), Camarena (2020), Chamara et al. (2020), Chandra and Collis (2021), Concepcion et al. (2021), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022), Dayioglu and Turker (2022), Dorin et al. (2022), Elbehri and Chestnov(2021), Escamilla-García et al. (2020), Everingham et al. (2016), FAO (2020), Feng et al. (2019), Fenu and Malloci (2019), Fenu and Malloci (2022), Fiehn et al. (2018), Fikar (2018), Galaz et al. (2021), Gandhi et al. (2016), García Pereira et al. (2020), Garske et al. (2021), Gonzalez-de-Santos et al. (2020), Guru and Mallikarjuna (2010), Heldreth et al. (2021), Holzinger et al. (2022), Hungilo et al. (2019), Hussain et al. (2021), Ingram and Maye (2020), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Jung et al. (2021), Kalyanaraman et al. (2022), Kim et al. (2020), Klerkx and Rose (2020), Kour and Arora (2020), Kugler (2022), Liakos et al. (2018), Linaza et al. (2021), Liu et al. (2022), López-Correa et al. (2022), MacPherson et al. (2022), Marinoudi et al. (2019), Marvin et al. (2022), Masi et al. (2021), Mohr and Kühl (2021), Ofori and Gayar (2020), Orn et al. (2018), Panchbhaiyye and Ogunfunmi (2018), Park et al. (2018), Ryan (2022), Saheb et al. (2022), Saiz-Rubio and Rovira-Más (2020), Schoormann et al. (2021), Shankar et al. (2020), Singh (2018), Siregar et al. (2022), Song et al. (2016), Spanaki et al. (2022a), Sparrow et al. (2021), Suh et al. (2018), Van Klompenburg et al. (2020), Vinuesa et al. (2020), Wang et al. (2022)
Economic sustainability	Banjeree (2020), Camarena (2020), Dorin et al. (2022), Everingham et al. (2016), Gandhi et al. (2016), Garske et al. (2021), Gonzalez-de-Santos et al. (2020), Holzinger et al. (2022), Jung et al. (2021), Kim et al. (2020), Klerkx and Rose (2020), Linaza et al. (2021), MacPherson et al. (2022), Magalhães et al. (2022), Marinoudi et al. (2019), Newlands et al. (2019), Nyéki et al. (2021), Ooge and Verbert (2022), Orn et al. (2018), Van Klompenburg et al. (2020), Vinuesa et al. (2020)
Social sustainability	Banjeree (2020), Chandra and Collis (2021), Dorin et al. (2022), Fikar (2018), Galaz et al. (2021), Holzinger et al. (2022), Kim et al. (2020), Klerkx and Rose (2020), MacPherson et al. (2022), Masi et al. (2021), Orn et al. (2018), Ryan (2022), Sharma (2021), Van Klompenburg et al. (2020), Vinuesa et al. (2020)

Table A5. Results for Human-AI Complementarity

Human-in-the-loop	Dorin et al. (2022), FAO (2020), Holzinger et al. (2022), Jagatheesaperumal et al. (2021), Kalyanaraman et al. (2022), Kamyshova et al. (2022), Linaza et al. (2021), Ogawa et al. (2021), Schöning and Richter (2021), Shankar et al. (2020), Sparrow et al. (2021), Viani et al. (2017), Vinuesa et al. (2020), Wang et al. (2022)
Human-centered AI	Basso and Antle (2020), Bonaccorsi et al. (2017), Camarena (2020), Chamara et al. (2020), Chandra and Collis (2021), Dadi et al. (2021), Dorin et al. (2022), Fenu and Malloci (2022), Fikar (2018), Heldreth et al. (2021), Holzinger et al. (2022), Ingram and Maye (2020), Kalyanaraman et al. (2022), Klerkx and Rose (2020), Kugler (2022), Marinoudi et al. (2019), Metta et al. (2022), Ogawa et al. (2021), Ooge and Verbert (2022), Orn et al. (2018), Panchbhaiyye and Ogunfunmi (2018), Park et al. (2018), Rao et al. (2021), Roshanianfard et al. (2020), Sharma (2021), Singh (2018), Vinuesa et al. (2020), Wang et al. (2022)

Table A6. Results for Social Roadblocks

Trust	Abbasi et al. (2022), Atwal et al. (2021), Chandra and Collis (2021), FAO (2020), FAO (2018), Ferrari et al. (2022), Guillén-Navarro et al. (2020), Heldreth et al. (2021), Holzinger et al. (2022), Jagatheesaperumal et al. (2021), Lezoche et al. (2020), MacPherson et al. (2022), Mohr and Kühl (2021), Ooge and Verbert (2022), Orn et al. (2018), Ryan (2022), Saheb et al. (2022), Spanaki et al. (2022a), Sparrow et al. (2021)
AI unawareness	Atwal et al. (2021), Bahn et al. (2021), Banjeree (2020), Chamara et al. (2020), Benos et al. (2021), Chandra and Collis (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022), FAO (2020), FAO (2021a), FAO (2021b), Ferrari et al. (2022), Garske et al. (2021), Heldreth et al. (2021), Holzinger et al. (2022), Kalyanaraman et al. (2022), Lezoche et al. (2020), Linaza et al. (2021), Marinoudi et al. (2019), Metta et al. (2022), Ooge and Verbert (2022), Orn et al. (2018), Raju et al. (2006), Rao et al. (2021), Santos Valle and Kienzle (2020), Shankar et al. (2020), Sharma et al. (2021)
AI use uncertainty	Abbasi et al. (2022), Abioye et al. (2022), Bhat and Huang (2021), Cravero et al. (2022), Ferrari et al. (2022), Gerhards et al. (2022), Heldreth et al. (2021), Klerkx and Rose (2020), Linaza et al. (2021), Mohr and Kühl (2021), Ooge and Verbert (2022), Raju et al. (2006), Abbasi et al. (2022), Abioye et al. (2022), Guillén-Navarro et al. (2020), Kelly et al. (2022), Kumar et al. (2020), Sharma et al. (2021), Spanaki et al. (2022b), Sparrow et al. (2021), Van Klompenburg et al. (2020)
Resource constraints	Araújo et al. (2021), Abioye et al. (2022), Alexandrova et al. (2021), Atwal et al. (2021), Bahn et al. (2021), Benos et al. (2021), Bestelmeyer et al. (2020), Bhat and Huang (2021), Camarena (2020), Chamara et al. (2020), Chandra and Collis (2021), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dadi et al. (2021), Dayioglu and Turker (2022), Dhanya et al. (2022), Escamilla-García et al. (2020), FAO (2018), FAO (2021a), Ferrari et al. (2022), Garske et al. (2021), Gerhards et al. (2022), Galaz et al. (2021), Heldreth et al. (2021), Henkhaus et al. (2020), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Kalyanaraman et al. (2022), Kamyshova et al. (2022), Klerkx and Rose (2020), Kour and Arora (2020), Lezoche et al. (2020), Linaza et al. (2021), Marinoudi et al. (2019), Marvin et al. (2022), Metta et al. (2022), Mohr and Kühl (2021), Mugiyo et al. (2021), Ooge and Verbert (2022), Raju et al. (2006), Rao et al. (2021), Ryan (2022), Saggi and Jain (2022), Sharma (2021), Sharma et al. (2021), Siregar et al. (2022), Spanaki et al. (2022b), Vinuesa et al. (2020), Wang et al. (2022)

Table A7. Results for Systems Roadblocks

Interoperability	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Basso and Antle (2020), Benos et al. (2021), Bestelmeyer et al. (2020), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), FAO (2020), Ferrari et al. (2022), Henkhaus et al. (2020), Holzinger et al. (2022), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Kour and Arora (2020), Lezoche et al. (2020), Linaza et al. (2021), Metta et al. (2022), Rao et al. (2021), Ryan (2022), Siregar et al. (2022), Van Klompenburg et al. (2020),
Black box	Benos et al. (2021), Cravero et al. (2022), Dara et al. (2022), Dayioglu and Turker (2022), FAO (2020), Fenu and Malloci (2022), Fiehn et al. (2018), Garske et al. (2021), Heldreth et al. (2021), Holzinger et al. (2022), Hussain et al. (2021), Jagatheesaperumal et al. (2021), Liu et al. (2020), MacPherson et al. (2022), Metta et al. (2022), Orn et al. (2018), Ryan (2022), Saheb et al. (2022), Schöning and Richter (2021), Siregar et al. (2022)
Non-user friendly	Abbasi et al. (2022), Abioye et al. (2022), Banjeree (2020), Benos et al. (2021), Bhat and Huang (2021), Bonaccorsi et al. (2017), Cravero and Sepúlveda (2021), Dara et al. (2022), Dayioglu and Turker (2022), FAO (2020), FAO (2021a), Feng et al. (2019), Ferrari et al. (2022), Heldreth et al. (2021), Holzinger et al. (2022), Liu et al. (2020), Liu et al. (2022), MacPherson et al. (2022), Mohr and Kühl (2021), Saggi and Jain (2022), Santos Valle and Kienzle (2020), Trendov et al. (2020)
Algorithmic bias	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Basso and Antle (2020), Bestelmeyer et al. (2020), Chandra and Collis (2021), Concepcion et al. (2021), Bhat and Huang (2021), Camarena (2020), Cowls et al. (2021), Cravero and Sepúlveda (2021), Cravero et al. (2022), Dara et al. (2022), Dhanya et al. (2022), Elavarasan and Vincent (2020), Everingham et al. (2016), Fenu and Malloci (2022), Fiehn et al. (2018), Fikar (2018), Galaz et al. (2021), Guillén-Navarro et al. (2020), Heldreth et al. (2021), Henkhaus et al. (2020), Jagatheesaperumal et al. (2021), Kamyshova et al. (2022), Khan et al. (2022), Kim et al. (2020), MacPherson et al. (2022), Magalhães et al. (2022), Marvin et al. (2022), Park et al. (2018), Ridwan et al. (2021), Ryan (2022), Schöning and Richter (2021), Sharma (2021), Singh (2018), Suh et al. (2018) Vinuesa et al. (2020), Wang et al. (2022)

Table A8. Results for Deployment Roadblocks

Generalizability	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Bestelmeyer et al. (2020), Bhagat et al. (2022), Cravero et al. (2022), Dhanya et al. (2022), Dorin et al. (2022), FAO (2020), Fenu and Malloci (2022), Fiehn et al. (2018), Fikar (2018), Galaz et al. (2021), Guillén-Navarro et al. (2020), Hungilo et al. (2019), Hussain et al. (2021), Holzinger et al. (2022), Kalyanaraman et al. (2022), Lezoche et al. (2020), Linaza et al. (2021), Ooge and Verbert (2022), Park et al. (2018), Shankar et al. (2020), Trabelsi et al. (2022), Wang et al. (2022)
Transfer context bias	Bahn et al. (2021), Bhat and Huang (2021), Cravero et al. (2022), Dadi et al. (2021), Galaz et al. (2021), Hussain et al. (2021), Kalyanaraman et al. (2022), Kour and Arora (2020), Lezoche et al. (2020), Nguyen et al. (2011), Ooge and Verbert (2022), Rao et al. (2021), Trendov et al. (2020)

Table A9. Results for Ethical Roadblocks

AI risks	Abbasi et al. (2022), Abioye et al. (2022), Araújo et al. (2021), Bahn et al. (2021), Banjeree (2020), Bhat and Huang (2021), Bonaccorsi et al. (2017), Chandra and Collis (2021), Cowls et al. (2021), Cravero et al. (2022), Dadi et al. (2021), Dara et al. (2022), Dhanya et al. (2022), FAO (2020), FAO (2021a), Ferrari et al. (2022), Galaz et al. (2021), Garske et al. (2021), Heldreth et al. (2021), Holzinger et al. (2022), Ingram and Maye (2020), Jagatheesaperumal et al. (2021), Javaid et al. (2022), Klerkx and Rose (2020), Lezoche et al. (2020), Linaza et al. (2021), Liu et al. (2022), MacPherson et al. (2022), Marvin et al. (2022), Metta et al. (2022), Mohr and Kühl (2021), Mugiyo et al. (2021), Ooge and Verbert (2022), Rao et al. (2021), Ryan (2022), Saheb et al. (2022), Santos Valle and Kienzle (2020), Sharma et al. (2021), Spanaki et al. (2022a), Spanaki et al. (2022b), Sparrow et al. (2021), Trendov et al. (2020), Vinuesa et al. (2020)
AI ethics	Atwal et al. (2021), Bhagat et al. (2022), Cowls et al. (2021), Dara et al. (2022), Dhanya et al. (2022), Ferrari et al. (2022), Galaz et al. (2021), Garske et al. (2021), Holzinger et al. (2022), Kalyanaraman et al. (2022), Kelly et al. (2022), Kugler (2022), MacPherson et al. (2022), Marinoudi et al. (2019), Marvin et al. (2022), Metta et al. (2022), Ofori and Gayar (2020), Ooge and Verbert (2022), Ryan (2022), Vinuesa et al. (2020)

Table A10. Representative Examples for Each Theme for RQ1 Extracted from Sample Literature

Theme	Second order concepts	Quotes
AI resource	AI techniques	In our experiments, the AI model (CNN) was trained with large disease datasets, created with plant images self-collected from many farms over 7 months. Test images were diagnosed using the automated CNN model and the results were validated by plant pathologists. (Singh, 2018)
	AgriDSS design and development phase	We designed and implemented a prototype system that detects and classifies object image of strawberry using the YOLO v2 algorithm and Darknet in order to decide harvesting time of strawberries. (Kim et al., 2020) FAMEWS can be downloaded free of charge from the Google Play store. There are almost 10 000 registered FAMEWS users. (FAO, 2020)
AI capabilities	Situation awareness	The context-aware fertilizer recommendation is implemented with the Logistic Regression (LR), Support Vector Machine (SVM), Gaussian Naïve Bayes (GNB), and K-Nearest Neighbor (KNN) machine learning models to assess the performance of these machine learning models. (Khan et al., 2022)
	Pattern recognition	Deep learning is a subset of Artificial Intelligence, which has become popular in recent years to perform tasks like image classification, speech recognition, etc. (Panchbhaiyye & Ogunfunmi, 2018)
	Action	The application provides recommendations on dates for different agricultural practices, use of herbicides and insecticides, and other techniques to improve productivity. (Bahn et al., 2021)
	Learn	Learning ability Artificial Intelligence, goes a step further by not simply applying pre-programmed decisions, but instead exhibiting some learning capabilities. (Lezoche et al., 2020)
Type of tasks	Agricultural tasks	In order to apply on-the-spot herbicide spraying, robotic weeding, or precise mechanical weed control, it is necessary to identify crop plants and weeds. This work evaluates a novel method to automatically detect and classify, in one step, the most problematic weed species of tomato crops. (López-Correa et al., 2022)
	Sustainability goals	Improving the economic, social, and environmental sustainability of agri-food supply chains (AFSCs) is of paramount importance, given the impact of AFSC on the survival of mankind and of the planet. (Masi et al., 2021)
Task augmentation	Agricultural task efficiency	The fuzzy model inside the FDSS yields an estimate of the soil moisture based on the growing degree days (GDD), total water applied to the crop, and crop evapotranspiration (ETc). (Giusti & Marsili-Libelli, 2015)
	Sustainability goal efficiency	The numerical validation and the experiments performed in a vineyard in the north of Italy point out a considerable water saving with respect to other state-of-the-art methods based on parameters thresholding, and an improved exploitation of the irrigated water thanks to the reduction of the percolation phenomenon without affecting the quality of the crops. (Viani et al., 2017)
Human-AI complementarity	Human-in-the-loop	Moreover, the authors also addressed the ML-based interactions in the manufacturing process that occurs between machines and human operators by providing the platform for humans to be an in-the-loop technique with reduced errors. (Jagatheesaperumal et al., 2021)
	Human-centered AI	We suggest that further research is required into what human (and end-user)-centered AI systems could look like, focusing on aspects such as real-time computation, understandability, explanations for lay persons, and predictability of robot behavior in general. (Holzinger et al., 2022)

Table A11. Representative Examples for each Theme for RQ2 Extracted from Sample Literature

Theme	Second order concepts	Quotes
Social roadblocks	Trust	Many application domains call for increasing end users' trust in algorithmic decision making of DSSs, including agrifood. (Ooge & Verbert, 2022)

	AI unawareness	The need for more farmers of the future and the rise of AI in precision agriculture presents a promising opportunity for education. It is important for farmers to learn to utilize and trust AI technologies in their farming operations. (Orn et al., 2020)
	AI use uncertainty	In agriculture, the profit margin is very important like other sectors. When it comes to the implementation of advanced technologies, farmers have concerns related to the time to recover the investment and to the difficulties in evaluating the advantages (Abbasi et al., 2022)
	Resource constraints	These farmers share certain challenges, such as unreliable Internet and limited access to capital, with smallholder farmers in the developed world. (Heldreth et al., 2021)
Systems roadblocks	Interoperability	There is still little concern about using standards and formats that allow the exchange of information, in addition to interoperability. (Cravero & Sepúlveda, 2021)
	Black box	In the scope of explaining black-box algorithms, trust is thus heavily studied in XAI and visual analytics (Ooge & Verbert, 2022)
	Non-user-friendly	For example, if an AI tool cannot provide actionable recommendations to help farmers, the system is not user friendly and may be defective in terms of design and usability. (Dara et al., 2022).
	Algorithmic bias	Most data-driven approaches to AI are supervised, i.e., they are “trained” on existing labelled data as a basis from which to “learn” to cluster, classify, predict or make decisions regarding new, previously unseen data. This introduces the potential for unwanted bias to enter into the decisions at which an AI system ultimately arrives. (Cowls et al., 2021)
Deployment roadblocks	Generalizability	We began studies by using built-in capabilities (pictures of local birds) only to learn that laboratory training is not sufficient for especially accurate field identification. We then focused on training the system with images that would be closer to what an outside mounted camera might see. (Fiehn et al., 2018)
	Transfer context bias	The use of simpler forest monitoring and carbon sequestration models has already led to controversies partly due to their tentative transfer context bias (Galaz et al., 2021)
Ethical roadblocks	AI risks	Except for data quality, data privacy is an emerging challenge, as often serious threats arise primarily in the use of IoT and smart devices, along with trust and shared responsibility among the actors and entities involved. (Spanaki et al., 2022a)
	Ethical issues	Dynamic pricing decisions by the artificial agents, however, are usually invisible to humans which also leads to social and ethical concerns regarding algorithmic responsibility and accountability (Marvin et al., 2022)

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