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Understanding technology acceptance in smart agriculture: A systematic review of empirical research in crop production

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ABSTRACT

Smart agriculture offers the potential to analyse agricultural data at a scale not previously possible. Researchers argue that the combination of rich data and intelligent decision support has the potential to improve productivity and profitability in agriculture, whilst also improving sustainability. We argue that achieving this potential requires not just on technological advancement, it also requires a detailed understanding of factors that impact technology acceptance in smart agriculture. Acceptance is necessary if technical advances are to translate into real-world impact. However, technology acceptance is complex and often poorly understood. This systematic review focuses on technology acceptance in prediction and decision support systems in crop production. Major databases were searched to identify papers that formally address technology acceptance and include detailed data. 16 papers met the inclusion criteria and were included in the final analysis. Common facilitators and barriers are identified, and papers are mapping against the Theoretical Framework of Acceptability. This analysis showed that constructs including perceived effectiveness are addressed frequently, but others such as opportunity costs and burden have received less attention. The findings suggest the necessity for greater application of formal methods and the need for standardized, domain-specific methods to support this assessment.

1. Introduction

The last decade has witnessed rapid advancement in information and communication technologies (ICTs) that have the potential to significantly disrupt traditional agricultural practices. These technological advances offer new strategies to gather, process and analyse temporal, spatial, and individual data in a manner, and at a scale, not previously possible (O'Grady and O'Hare, 2017). Combining data-rich approaches with computational modelling and intelligent decision support offers the potential for improved efficiency, driving productivity and profitability, whilst also addressing the need for increased sustainability in agricultural production.[1] Reflecting this potential, the market for smart agricultural technologies was estimated at 13.7 billion in 2020 and is projected to reach 22.0 billion by 2025.[2]

In this paper we argue that achieving the potential of smart agriculture is dependent not just on technological advances, it is equally dependent on the degree to which new technologies are acceptable to the broad range of stakeholders that make up the agricultural community. Technology acceptance is a complex phenomenon, which goes beyond single issues such as usability or the cost of technology. It is something which has explored in detail in societally important domains such as healthcare, banking, and e-commerce (June et al., 2003). Previous research has found that while acceptance is widely recognised as important in smart agriculture, the methods through which it is addressed and understood are often poorly defined (Lowenberg-DeBoer and Erickson, 2019). This paper seeks to addresses this gap. Using a systematic review approach, it explores the strategies used to assess technology acceptance in smart agriculture and identifies common barriers and facilitators to acceptance. It also maps prior work against an accepted theoretical model of technology acceptance, the Theoretical Framework of Acceptability (Sekhon et al., 2017). We focus specifically on acceptance of prediction and decision support systems in crop production. This decision allowed us to manage the overall scope of the review, but also reflected our own core interest in crop farming. However, prediction and decision support systems incorporate key elements of smart agriculture, including the use of rich data and machine learning to support day-to-day decision making in food production. As such the lessons learned will also have relevance to other areas within smart agriculture.

People typically have an instinctive understanding of words such as

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1 https://www.ispag.org/about/definition

2 https://www.marketsandmarkets.com/Market-Reports/smart-agriculture-market-239736790.html

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acceptability and acceptance. For example, The Oxford Dictionary defines acceptability[3] as *'the quality of being acceptable'* and acceptance[4] as 'belief in or agreement with an idea, theory, statement, etc'. More broadly there are a myriad of terms used in relation to acceptance, including acceptability, adoption and even usability. Sometimes these terms are used interchangeably within the literature. It is therefore important to clarify at the outset how technology acceptance is defined in this paper. (Nadal et al., 2020) argue that acceptability from the end-user[5] point of view is dependent on the degree to which an object is suitable, and acceptance is the process the user goes through in relation to the specific technology. The review of acceptance in this paper is grounded in an established theoretical model of acceptance, the Theoretical Model of Acceptance or Theoretical Framework of Acceptability (Sekhon et al., 2017). This model, like other theoretical models of acceptance (see Section 2), goes beyond instinctive or narrowly defined interpretations of acceptance and instead provides rigorous methods to unpick different constructs underlying acceptance.

The paper addresses the following research questions:

1. What are the key facilitators and barriers to user acceptance of decision support systems in crop farming?
2. To what extent do prior studies of acceptance map to theoretical models of technology assessment, in particular the Theoretical Framework of Acceptability?
3. What recommendations can be provided for further steps toward the development of formal technology acceptance methods in smart agriculture?

This paper makes several contributions. It identifies the common barriers and facilitators to technology acceptance in smart agriculture. As noted, the focus in on intelligent decision support systems in crop farming. To the best of authors' knowledge, this is first paper to provide a systematic review of technology acceptance in this area. We find that, with notable exceptions, researchers in this domain have primarily studied individual constructs of acceptance, often in a relatively informal manner and without linking to formal models. This highlights the profound need for a standardized method or model by which to assess technology acceptance in crop farming, and in smart agriculture more generally. Defining such as method or model is beyond the scope of this paper, but it provides rigorous foundations for this future work.

2. Models, theories and frameworks of technology acceptance

Within research several specific models and frameworks have been developed to support the rigorous investigation of technology acceptance. A full review of these theories is beyond the scope of this paper. Some theories, such as the Theory of Planned Behaviour, the Theory of Reasoned Action and the Theoretical Domains Framework and the related theories or frameworks, apply principles, reasons or beliefs pertaining to user motivation and behaviour changes (Armitage and Christian, 2003; Atkins et al., 2017), and have been adapted to address technology acceptance. We do not apply these theories in this paper, as the study of acceptance was not core motivation for their development. We have also omitted value-based models, such as the Value-Belief-Norm Theory, as they cover a narrower set of constructs compared the two models discussed below, and place greater emphasis on adoption rather than acceptance (Stern et al., 1999; Steg et al., 2005; Stern, 2000; Jansson et al., 2011; van der Werff and Steg, 2016). In this paper we highlight on two prominent models: the Technology Acceptance Model (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008; Teo, 2016), and the Theoretical Model of Acceptance or Theoretical Framework of Acceptability (Sekhon et al., 2017). Each model provides an empirically grounded set of constructs specifically focused on acceptance and each places users at the central point of investigation. Ultimately the second of these models is applied in this paper, for several reasons.

The ***Technology Acceptance Model (TAM)*** and its extended models focus on the system, the user, and on actual use (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008; King and He, 2006). It considers features and capabilities of the system that effects the user's motivation toward the system. TAM adopts a holistic approach considering a broad range of factors effecting system acceptance that can be measured as perceived usefulness, ease of use and intended use of the system. Empirical studies which adopt TAM measure the different constructs of acceptability quantitatively. TAM can be used to help understand the factors of technology acceptance and help to identify interventions that can favourably influence these factors. However, while successful and widely used, this model does have limitations. Given the statistical methods involved, TAM requires large sample sizes to yield statistically valid or significant results. Due to this research studies have often used a convenient research sample population of students who are neither the professionals, the targeted user group, or a general population, thus compromising such experiments. TAM has also been criticised as lacking in practical value (Chuttur, 2009) and for focusing too narrowly on the interaction between the user and the technology, at the expense of broader considerations of the contextual and societal aspects of technology acceptance (Benbasat and Barki, 2007). Due to the quantitative nature of data collection, TAM does not encourage the capture or rigorous analysis of qualitative data, such as feedback from users in the form of suggestions, opinions and supporting reasons for their choices or attitudes.

In this paper we directly apply a more recently developed framework for acceptance, the Theoretical Model of Acceptance or ***Theoretical Framework of Acceptability (TFA)***. The TFA provides an alternative to the TAM, placing greater emphasis on the analysis of both quantitative and qualitative data. It provides a structured and data-based analysis which rigorously considers seven empirically derived dimensions of acceptance (Sekhon et al., 2017). These dimensions were initially formulated from a literature review of acceptability in implementations of healthcare interventions, but they have widespread applicability and are based on a wider set of user subjective beliefs about value of interventions (Rooksby et al., 2019; Rushton et al., 2020; Brook et al., 2020; Breault et al., 2019). The seven dimensions are (1) Affective Attitude, which describes how users feel about the system; (2) Burden, which describes the perceived amount of effort needed to use the system; (3) Ethicality, which describes the degree to which the system blends in with the user's value system; (4) Intervention/System Coherence, which describes the degree to which the user understands the system and it's working; (5) Opportunity Costs, which captures what (and the degree to which) the user must be relinquish in order to use the system; (6) Perceived Effectiveness, which describes the degree to the users perceive the system as delivering anticipated results; and (7) Self Efficacy, which describes if the users are sufficiently confident to make the necessary behaviour changes required by the system. These seven dimensions considers prospective, concurrent and retrospective acceptability.

The mapping of technology acceptance presented in the Findings section of this paper is based on the TFA. This decision was based on two main factors: (1) the consideration it provides for a broader range of constructs; and (2) support for the use of both quantitative and qualitative data. These these factors combine to give the TFA greater practical value in the context of this review.

[3] https://www.oed.com/view/Entry/1007?redirectedFrom=acceptability#eid

[4] https://www.oed.com/view/Entry/1011?redirectedFrom=acceptance#eid

[5] In the context of this paper the term 'end-user' describes the broad range of stakeholders who will potentially use smart agricultural technologies. This includes farmers, agronomists and farm managers, but can also include wider stakeholders groups such as analysts who make use of the data, computational modelling and decision support systems enabled by smart agriculture.

Table 1
Eligibility criteria for systematic review, focusing on prediction and decision support in crop farming.

	Inclusion criteria	Exclusion criteria
Population	Minimum age of 18 years Participants who have or had a farming or agricultural (crops) background, e.g., farmers, farm managers, agronomists	Children Not farming or agricultural (crops) related
Intervention type	Technology-enabled interventions (e.g., apps, websites, tools that assess crop farming technology acceptance) used by the participants Technology-enabled apps, e.g., interventions and their impact on such as soil improvement or crop production Online resources that improve crop yields	Diagnostics interventions (e.g., soil sampling) Technology-enabled interventions not directly relevant population
Study type	Qualitative and quantitative studies exploring technology acceptance, which includes effectiveness, usability, user experience and design of a technology-based intervention (e.g., RCTs, cohort studies, case-control, case series, quasi-experimental studies etc…)	Study Protocols Opinion pieces Review papers
Outcome measures	Technology acceptance data such as usability, user experience and/ effectiveness in crop farming	Absence of technology acceptance data in crop farming
Study analyses	Qualitative or qualitative data and analysis of outcome data	No analysis of data reported
Publication criteria	Human studies Published in peer-reviewed journals and archival conference proceedings Published in the English language	Published in a language other than English with absence of peer-reviewed translation to English

3. Methodology

This section describes the methodology applied in the systematic review. The selection procedures were based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) Statement (Moher et al., 2009).[6] PRISMA provides a rigorous approach to review studies. It has been widely applied to systematic reviews in health settings but is also increasingly applied in other domains.

3.1. Eligibility criteria

The PICO (Population Intervention Comparison and Outcome) acronym (Methley et al., 2014) was used to refine the eligibility criteria for the review. Table 1 outlines the eligibility criteria on which this review was based. Our focus was on evidence-based research of technology acceptance in crop farming. Rather than exploring technology in a broad sense, the paper focused on literature describing intelligent prediction and decision support systems. This decision reflected our own core interests. However, it also reflects the fact that while such systems are the focus of significant ongoing research, they have not yet been widely adopted in day-to-day practice (Lowenberg-DeBoer and Erickson, 2019). As will be seen this focus still resulted in several thousand papers being returned in the initial search. Studies were eligible for inclusion if they reported data related to technology acceptance and if the paper reported qualitative or quantitative data. Studies that did not report or analyse data were excluded.

3.2. Search strategy

Papers were identified by performing an online search of journal articles and conference proceedings from the following databases: the ACM Digital Library, Scopus, CABI and Business Source Complete (EBSCOhost). The CABI database was included as it is dedicated to agriculture and the EBSCOhost database was included as it also covers topics in agriculture. The ACM Digital Library was included as it is a core archival library for computer science research. Both Scopus and ACM Digital Library included results from IEEE Xplore and have publications in areas combining computer science and agriculture. The search strategy used for each database was based on the keywords listed in Table 2 relating to (1) Agriculture, (2) Technology-enabled interventions and (3) Acceptance. For ‘Agriculture’ we used the obvious term ‘agriculture’, its synonyms ‘farm’ and ‘crop’ as our focus was on crop farming. For ‘Technology-enabled Intervention’ we used terms that can be related to smart farming. For Acceptance, we used variations of the word acceptance and related terms. Each search was conducted for keywords in the paper titles, abstracts and/or author keywords. The search strategy also included individual database index terms.

Given the diverse nature of the databases it was necessary to adapt the search terms on a case-by-case basis. For example, the ACM Digital Library is a database of computer science research, therefore the search did not include keywords from the ‘technology-enabled interventions' as this was already implied. The keywords used for Scopus, Business Source Complete and CABI are similar. The final search terms used in each database were as follows:

ACM Digital Library: "query: Abstract:(agricultur* OR crop* OR farm*) AND Abstract:(accept* OR adopt* OR usab*) “filter“: Publication Date: (01/01/2009 TO 12/31/2020) "
Scopus: (TITLE-ABS-KEY (agricult* OR farm* OR crop*) AND TITLE-ABSKEY (web-base* OR online OR internet OR mobile OR “smart farm*“ OR “smart agricult*“OR “IoT“ OR comput* OR “decision support“ OR visuali* OR “machine learn*“ OR “precision agricult*“) AND TITLEABS-KEY (accept* OR adopt* OR usab*)) AND PUBYEAR > 2009
CABI & Business Source Complete: ab:(agricult* OR farm* OR crop*) AND ab:(web-base* OR online OR internet OR mobile OR “smart farm*“ OR “smart agricult*“ OR “IoT“ OR comput* OR “decision support“ OR visuali* OR “machine learn*“ OR “precision agricult*“) AND ab:(accept* OR adopt* OR usab*) yr:[2009 TO 2020]

3.3. Screening and selection

The full screening process is detailed in Table 3. As can be seen the search of the ACM Digital Library retrieved 1276 documents. The search of Scopus retrieved 5781 documents. The CABI search retrieved 2286 documents and the search of Business Source Complete retrieved 290 documents. Following the PRISMA guidelines screening took place in two stages: (1) initial screening by title and abstract, and (2) full text screening. Screening was conducted separately for each database. It was led by the first author and papers we included or excluded based on the

Table 2
Keywords used in database searches in systematic review.

Agriculture	agriculture* OR crop* OR farm*
Technology-enabled Intervention	“web base*” OR online OR “smart farm* OR internet OR comp* OR “smart agricult*” OR “IoT” OR “decision support” OR “machine learn*” OR “precision agricult” OR “visuali*”
Acceptance	accept* OR adopt* OR usab*

[6] http://prisma-statement.org

Table 3
Paper screening process adapted to the PRISMA statement (Moher et al., 2009). Note: the initial screening of Scopus and CABI databases involved two steps. Step 1 used database filters. Step 2 was done manually using JabRef software. For the ACM Digital Library and Business Source Complete databases all initial screening was done manually using JabRef.

	ACM Digital Library	Scopus	CABI	Business Source Complete
Search date	May 15th, 2020	May 28th, 2020	June 22nd, 2020	June 22nd, 2020
Records identified through search	$n = 1276$	$n = 5781$	$n = 2286$	$n = 290$
Initial screening by title and abstract	Records screened manually (n = 1276) Records excluded: ($n = 944$)	Step 1: Screening using database filters (n = 5781) Records excluded: Not related to farming/ agriculture (crops) ($n = 2940$) Background study/ models/work in progress/ /review/editorial papers ($n = 300$) Not in English language ($n = 712$) Duplicates ($n = 201$) Step 2: Records screened manually ($n =$ 1628) Records excluded: ($n = 1470$)	Step 1: Screening using database filters (n = 2286) Records excluded: Not related to farming/agriculture (crops) ($n = 509$) Background study/ models/work in progress/ review/ editorial papers ($n = 532$) Not in English language ($n = 276$) Duplicates ($n = 164$) Step 2: Records screened manually ($n = 805$) Records excluded: (n = 712)	Records screened manually (n = 290) Records excluded: Discussion/ editorial papers (n = 79) Not related to farming/ agriculture (crops) ($n = 189$) No full text available ($n = 19$)
Full-text articles assessed for eligibility	Articles screened $n = 332$ Articles excluded: Not within target population (n = 5) Limited access to full text ($n = 26$) DOI not found/not available online ($n = 39$) Not related to farming/agriculture (crops) ($n = 10$) Background study/ models/ work in progress/ discussion/ review papers ($n = 83$) Absence of technology acceptance data/analysis in e-agriculture ($n =$ 138) Not used by relevant population (n = 10) Not in English language (n = 1) Retracted ($n = 2$)	Articles screened $n = 158$ Articles excluded: Not within target population ($n = 4$) Limited access to full text ($n = 5$) DOI not found/not available online (n = 5) Not related to farming/ agriculture (crops) (n = 2) Background study/ models/ work in progress/ discussion/ review/ editorial papers ($n = 40$) Absence of technology acceptance data/analysis in e-agriculture ($n = 69$) Not directly used by farmers/ agronomists ($n = 1$)	Articles screened $n = 93$ Articles excluded: Limited access to full text (n = 5) DOI not found/not available online ($n = 5$) Not related to farming/agriculture (crops) ($n = 3$) Background study/ models/ work in progress/ discussion/ review/ editorial papers ($n = 38$) Absence of technology acceptance data/analysis in e-agriculture ($n = 29$)	Articles screened n = 3 Articles excluded: Absence of technology acceptance data/analysis in e-agriculture (n = 3)
Articles included in final data screening	n = 18	$n = 32$	n = 13	$n = 0$
Final articles	Articles screened $n = 63$ Articles excluded $n = 47$ Articles included n = 16			

criteria listed in Table 1. At both screening stages, and across all databases, a random sample of 5 % of papers were re-examined by the last author. Where disparities were noted, they were resolved through discussion and subsequent double checking to ensure consistency. On completion of the full text screening 18 papers were included for the ACM Digital Library, 32 from Scopus, and 13 from CABI. No papers were included from Business Source Complete. This gave a total of 63 papers.

At this point the full set of remaining papers was merged and each paper was further assessed to understand the nature of the data included in the paper. The emphasis was on identifying papers that included detailed data related to technology acceptance. A further 47 articles was excluded at this point. Some articles were excluded as they primarily targeted a different population or user group, for example, users primarily from livestock farming with a minor interesting in crop farming (Fox et al., 2018; Michels et al., 2020b; Jarvis et al., 2017). Some articles reported limited data. For example, user evaluations were conducted, but very limited or no results are reported (Yang et al., 2011), or there was no clear link to technology acceptance (Kaloxylos et al., 2014; Alemu and Negash, 2015). Others reported only usability data without engaging with the issue of technology acceptance (Sciarretta et al., 2019; Lasso et al., 2018; Castro et al., 2019). Some articles reported solely on technology adoption in a broader sense, for example, to learn about agricultural practices (Sardar et al., 2019), use of SMS technology (Beza et al., 2018) and socio-cultural factors (Arvila et al., 2018) without addressing technology in the context of crop production. Other paper discussed smart agriculture adoption, but not acceptance, considering for example the timing of technology adoption (Watcharaanantapong et al., 2014), barriers of technology adoption (Aubert et al., 2012), and intention and attitude toward adoption (Rezaei-Moghaddam and Salehi, 2010; Tohidyan Far and Rezaei-Moghaddam, 2017). Final one paper described the development of a smart agriculture intervention, but no user evaluation was conducted (Di Giovanni et al., 2012).

4. Results

A total of 16 articles met the final criteria for inclusion in the analysis of barriers and facilitators to acceptance. Table 4 provides a summary of each paper and the key findings. Of the studies described two each were conducted in Australia, France, India, and Indonesia. Others ($n = 1$ each) were conducted in Brazil, China, Czech Republic, Germany, Italy, Philippines, Spain, and Thailand. Participant numbers ranged from 10 to 727, composed mainly of farmers and agronomists, but also including smaller groups such as lecturers, employees, researchers, and students. One article (Jakku and Thorburn, 2010) does not mention the number of participants. Quantitative and qualitative research methodologies were used across these research studies.

Table 4
Summary of articles included in final systematic review follow the screening process, including brief details of the methods applied and key findings.

Authors	Methods	Summary of article
Jakku and Thorburn (2010)	Participatory design and qualitative interview study.	Proposes a framework that emphasises participatory approaches in the development of smart agriculture. The framework combines the concepts of technological frames, interpretative flexibility, and boundary objects with social learning principles. The paper describes the use of this framework in the co-creation of decision support system for use in irrigation scheduling. Assessed the co-created system through interview studies with two farmer groups. One group favoured the decision support system, while the other did not.
Li et al. (2020)	Unified Theory of Acceptance and Usage of Technology Questionnaire	The Unified Theory of Acceptance and Usage of Technology, itself an extended version of **TAM**, was adapted to study farmers acceptance of precision agriculture technologies. Farmer perceptions of their own needs, the benefits of technology for farmers, accelerating conditions for technology adoption were the main factors that affected acceptance. The extent to which these factors align with technology characteristics had a substantial impact on the intention to adopt precision technologies among farmers.
Iskandar et al. (2018)	TAM questionnaire	Investigate the impact of farmer's knowledge, interest, learning materials, interaction, and awareness on technology acceptance. Using **TAM**, the analysed data represent farmers reaction in cognitive, affective, and psychomotor aspect in education which supported seven variables: Behavioural Intention, Attitude Toward, Perceived Usefulness, Subjective Norm, Self-Efficacy, Major Relevance, and System Accessibility. Perceived Ease of Use variable wasn't supported by user data.
Mackrell et al. (2009)	Field studies and semi-structured interviews	Qualitative case study of actual use of a decision support system (CottonLOGIC) in the Australian cotton industry. Technology was most successful when adapted and used in ways not anticipated by the developers. Increased adoption rates were maintained by a connected and co-related user element such as technology training and agronomy expertise.
Sayruamyat and Nadee (2020)	TAM questionnaire	**TAM** was used to investigate AgriMap, a mobile application that helps farmers to decide on crops to plant. Attitudes toward use was the only high significant factor in acceptance. Other constructs: perceived usefulness, perceived ease of use, result demonstrability, subjective norms, and intention to use have medium significance.
Ravier et al. (2018)	Participatory workshops	Applied participatory approaches to involve end user in the design and development of a system to support N fertilizer management. The system was tested with two groups of farmers. It was positively received and supported innovate fertilizer methods.
Souza et al. (2019)	TAM questionnaire	**TAM** was used to evaluate an integrated IoT based seed testing system (ColoT). The overall user approval rate was high for both the ease of use and the usefulness of the system. Some concerns were raised regarding automated alerts within the system and the need for further research is identified.
del Águila et al. (2015)	Usability and functionality questionnaire.	Developed Web-Pest, a rule-based web decision support system with integrated pest management to help with the pest control that is environmentally friendly. Evaluation focused on usability and the validation of rule-based system. Found to be particularly useful for inexperienced farmers and untrained technicians.
Rahim et al. (2016)	Usability questionnaire	Developed a smartphone application the uses case-based reasoning to automatically assess land suitability for rubber, cocoa, and oil palm tree crops. User evaluation focused on the usability of the app.
Caffaro et al. (2020)	TAM questionnaire	**TAM** was used to investigate two groups of technology: (1) drones, sensors for data acquisition and automatic download, and agricultural apps; (2) agricultural robots and autonomous machines. Perceived usefulness affects farmers' intention to adopt. Information from formal sources was found to increase perceived usefulness. In contrast information from informal sources reduced perceived usefulness.
Jain et al. (2018)	Comparative, task-based user study and interview	Developed FarmChat a conversational agent using cloud services to naturally converse and answer farming-related questions. It helped farmers with limited literacy and technology experience as the answers were specific and localized. It was generally well-accepted and trusted with willingness to continued use.
Mir and Padma (2020)	Novel survey developed	This paper proposes a new model for technology acceptance, specific to agricultural decision support systems: the Integrated Technology Acceptance Model. It focuses on addressing the technical, human, and organizational contextual factors that impact acceptance. The framework is been used to investigate users acceptance of a decision support system developed for insect-pest and nutrient management of apple.
Ayerdi Gotor et al. (2020)	Observational study and questionnaire	The actual farm level use of three technologies (Global Navigation Satellite Systems, section control, and variable rate application) was investigated using a structured interview developed by the authors. The final impact of technology is cluster in categories: economic, social and environmental. Recommends greater support by technical advisors or agro-equipment suppliers, increase of local references, as well as an increase in exchanges of information among farmers to boost collective learning.
Ulman et al. (2017)	Usability and quality in use questionnaire	Focuses on a national e-service agriculture management in the Czech Republic. Finds that the majority of the users were not satisfied with the quality of services provided. Improvements needed in usability, accessibility, and information management.
Michels et al. (2020a)	Unified Theory of Acceptance and Use of Technology Survey	The Unified Theory of Acceptance and Usage of Technology, itself an extended version of **TAM**, was used to study mobile decisions support apps. Perceived ease of use, effort expectancy and subjective norm had a significant effect on behavioural intention for actual use. Effort expectancy and subjective norm has a significant effect on perceived ease of use. Facilitating conditions did not have a significant effect on Behavioural Intention for adoption, had a significant effect on actual adoption
Mercurio and Hernandez (2020)	Extended TAM questionnaire	Used the extended TAM to investigate acceptance of a decision support system that classifies crop variety and disease using machine learning. This study also shows that security, reliability, and portability play a significant role in user acceptance. However, technological complexity does not affect perceived usefulness. This study confirms the impact of diverse factors on user acceptance of an information system and how factors interact.

Table 5
A summary of the facilitators of technology acceptance identified in 16 papers.

Facilitator of acceptance	No. of papers	Papers
A positive impact on productivity, time, and costs.	5	(Jakku and Thorburn, 2010) (Li et al., 2020) (Michels et al., 2020a) (Ravier et al., 2018) (Ayerdi Gotor et al., 2020)
Increased information and knowledge	5	(Jain et al., 2018) (Jakku and Thorburn, 2010) (Li et al., 2020) (Caffaro et al., 2020) (Ravier et al., 2018)
Support for training	4	(Li et al., 2020) (Jakku and Thorburn, 2010) (Mir and Padma, 2020) (Michels et al., 2020a)
Familiarity and market readiness	4	(Caffaro et al., 2020) (Jain et al., 2018) (Li et al., 2020) (Mir and Padma, 2020)
Effective support for daily practices	4	Li et al., 2020) (Michels et al., 2020a) (Mackrell et al., 2009) (Jakku and Thorburn, 2010)
Accuracy and reliability	3	Ayerdi Gotor et al., 2020) (Jain et al., 2018) (Mir and Padma, 2020)
Effective Decision support	3	(Jakku and Thorburn, 2010) Li et al., 2020) (Mackrell et al., 2009)
Personalised and localized information	2	(Jain et al., 2018) (Michels et al., 2020a).
Increased wellbeing	1	(Ayerdi Gotor et al., 2020)

4.1. Facilitators of technology acceptance

Facilitators for technology acceptance were discussed by nine studies with nine distinct categories identified. Table 5 shows these categories and the papers in which they were identified. Seven studies did not identify facilitators of technology acceptance (Iskandar et al., 2018; Sayruamyat and Nadee, 2020; Souza et al., 2019; del Águila et al., 2015; Rahim et al., 2016; Ulman et al., 2017; Mercurio and Hernandez, 2020).

The first facilitator, identified in five papers, focused on the positive impact technology can have on productivity and costs. Farmers were inclined to accept technology if it reduced overall farm costs and provided increased profits (Jakku and Thorburn, 2010; Li et al., 2020), helped to cut down on resources needed (Ravier et al., 2018), reduced dependence on external resources (Michels et al., 2020a), or reduced labour requirements (Ayerdi Gotor et al., 2020).

Increased information and knowledge were also identified as important in five papers. Farmers valued technology that provided useful information and guidance (Jain et al., 2018; Jakku and Thorburn, 2010; Li et al., 2020). Knowledge that helped farmers to modernize their current agricultural practices was highlighted by Ravier et al. (2018). While Caffaro et al. (2020) highlight the value of information with links to known organizations such as farmers' associations.

Related to information and knowledge, four papers also found that support for training enhanced technology acceptance (Li et al., 2020; Jakku and Thorburn, 2010; Mir and Padma, 2020; Michels et al., 2020a). This related to training in crop management techniques (Li et al., 2020), but training focused on the use of new technology was also valued (Mir and Padma, 2020; Michels et al., 2020a). For example, Jakku and Thorburn (2010) describe the importance of help to explore options and possible settings in technology that enables automation of manual processes.

Familiarity and market readiness was identified as important in four papers. Farmers who were familiar with similar technology (Jain et al., 2018) or had taken part in previous smart agriculture related research projects were more likely to accept new technology (Li et al., 2020; Michels et al., 2020a; Mir and Padma, 2020). Caffaro et al. (2020) note the importance of market readiness, describing the impact on farmers when technology used in a research project subsequently became unavailable.

A further four papers note the importance of effectively supporting day-to-day farming practices. Li et al. (2020) emphasise the importance of a clear fit to farming requirements. Michels et al. (2020a) extend this point and suggest that directly involving farmers in design and development process supports this aim and enhances acceptance. They also describe the need for clear communication on the benefits technology provides to farmers. Jakku and Thorburn (2010) highlight the benefits of automating manual processed, while Mackrell et al. (2009) note that this benefit can extend beyond in-field activities, giving the example of automated support for archiving and record keeping.

Given the focus of the review, it is unsurprising that effective decision support was a facilitator of acceptance, explicitly identified in three papers (Jakku and Thorburn, 2010; Li et al., 2020; Mackrell et al., 2009). What is more interesting however, is the ways in which effective support was described. Jakku and Thorburn (2010) describe decision support as advise or a second opinion. Mackrell et al. (2009) focus on how systems can help in decision making for agronomist, professionals, and trained farmers. The emphasis in both cases is on the user as the decision maker, with technology providing support.

Related to both day-to-day effectiveness and decision making, three papers noted the importance of accuracy and reliability to acceptance (Ayerdi Gotor et al., 2020; Jain et al., 2018; Mir and Padma, 2020). Technical efficiency and precision in the automated farm processes is valued (Ayerdi Gotor et al., 2020). It is also important that information provided had to be accurate and trustworthy (Jain et al., 2018; Mir and Padma, 2020). Jain et al. (2018) note that technology can be perceived negatively is it does not validate the knowledge of farmers.

Finally, personalisation and localisation were noted in two papers, with Jain et al. (2018) arguing for solutions that are specific to and solve localized farming problems, and Michels et al. (2020a) emphasizing the value of appropriate and personalised information. One study specifically noted improved wellbeing as a factor in the acceptance of technology (Ayerdi Gotor et al., 2020). Improvements in wellbeing were linked to potential time savings and thus reduced pressure on farmers.

4.2. Barriers to technology acceptance

Seven studies did not discuss barriers to technology acceptance (Iskandar et al., 2018; Souza et al., 2019; del Águila et al., 2015; Rahim et al., 2016; Mir and Padma, 2020; Mercurio and Hernandez, 2020). Across the remaining nine studies, six common barriers were identified (see Table 6).

The first barrier, identified in five papers, focuses on the technical

Table 6
A summary of barriers to technology acceptance identified in 16 papers.

Barrier	No. of papers	Identified in
Difficult or complex to use	5	(Mackrell et al., 2009) (Sayruamyat and Nadee, 2020) (Jain et al., 2018) (Ulman et al., 2017) (Michels et al., 2020a)
Infrastructure requirements for setup and use	5	(Jakku and Thorburn (2010) (Li et al., 2020) (Mackrell et al., 2009) (Sayruamyat and Nadee, 2020) (Michels et al., 2020a)
Lack of support	3	(Li et al., 2020) (Mackrell et al., 2009) (Jakku and Thorburn, 2010)
Not suited to farmers needs	3	(Jakku and Thorburn, 2010) (Michels et al., 2020a) (Mackrell et al., 2009)
Increased burden	3	(Mackrell et al., 2009) (Ravier et al., 2018) (Michels et al., 2020a)
Perceptions of technology	3	(Jain et al., 2018) (Li et al., 2020) (Caffaro et al., 2020)

infrastructure requirements and the associated costs. Jakku and Thorburn, 2010 highlight the costs involved at both the initial setup stage and for continued use. Similarly, Li et al. (2020) also notes the need for expensive equipment. Mackrell et al. (2009) and Sayruamyat and Nadee (2020) both found that farmers might currently rely on older technology and have limited access to the state-of-the-art sensing technology and high-end mobile devices. Michels et al. (2020a) further notes the lack of high-speed mobile broadband infrastructure on many farms.

Five papers also identify difficult or complexity in use as a significant barrier to acceptance (Mackrell et al., 2009; Sayruamyat and Nadee, 2020; Jain et al., 2018; Ulman et al., 2017; Michels et al., 2020a). Some papers highlight specific usability issues as poor navigation or disorganized information (Ulman et al., 2017), whereas other the discuss difficult in using decision support features (Mackrell et al., 2009).

Related to complexity of use, three papers describe the lack of support available for new technologies (Li et al., 2020; Mackrell et al., 2009; Jakku and Thorburn, 2010). Li et al. (2020) notes the limited availability of smart agriculture contractors and lack of support for the initial installation and maintenance of services. They also note broader lack of services to support modern farming approaches.

Three papers found that technologies did not address farming needs. Jakku and Thorburn, 2010 found that the use of scientific terminology could act as a barrier, suggesting an emphasis on the scientific and research interests of domain experts, rather than the local needs and situated knowledge of farmers. Michels et al. (2020a) found that tasks supported by smart technology are often trivial, and thus are not needed. Similarly, Mackrell et al. (2009) found that farmers have significant accumulated knowledge and experience, and often have ready access to agronomist, consultants, and specialist services such as spray operators. This reduces the need to smart technology.

In three papers, smart technology was found to create an increased burden or workload. In Mackrell et al. (2009) farmers felt they were required to record too much new information, which was seen as unproductive use of time. Ravier et al. (2018) also identify barriers related to the time required to take the measurements needed for smart agriculture. Michels et al. (2020a) found that frequent software updates also increased the burden on farmers.

The final major barrier, again identified in three papers, related to farmers' perception of technology. In one paper (Li et al., 2020) the perception of smart technology as ‘advanced’ was identified as a barrier to acceptance. Jain et al. (2018) found that initial overestimations of the capabilities of technology, followed by subsequent disappointment, had a negative impact. Caffaro et al. (2020) found initial perceptions of smart technology are more likely to be influenced by informal personal contacts and local sources, rather than actual technology developers or early technology adopters. As such wider community perceptions, when negative, become a potential barrier to acceptance, even when these perceptions are not grounded in actual experience of using smart technologies.

4.3. Models, theories and methods applied in shortlisted papers

Seven of the 16 papers considered in the final review made use of either the TAM, or an extended version of the TAM, including the Unified Theory of Acceptance and Use of Technology Survey (Li et al., 2020; Iskandar et al., 2018; Sayruamyat and Nadee (2020); Souza et al., 2019; del Águila et al., 2015; Caffaro et al., 2020; Michels et al., 2020a; Mercurio and Hernandez, 2020). As such they used survey-based methods and report statistical analysis of quantitative data. Whilst it is not always explicitly stated, it seems reasonable to assume that the authors of these papers define technology acceptance based on the TAM and its extended models. In some cases, however, the TAM was applied without first providing a detailed rational for its use or without consideration of alternative approaches to studying acceptance.

One paper (Mir and Padma, 2020) provides an explicit critique of the prior technology acceptance frameworks, including the TAM. Similar to the critique of the TAM identified in Section 2 of this paper, the authors argue that prior frameworks fail to take sufficient account of broader technical, human and organizational factors likely to impact on technology acceptance. In response they propose and provide a formative evaluation of a new model and corresponding survey tool called the Integrated Technology Acceptance Model. Again, the methods applied are survey based and supported by statistical analysis.

The remaining eight papers applied a range of methods and varied significantly in the degree to which they engaged with prior theory. Some addressed acceptance in a narrowly defined manner. For example, del Águila et al. (2015), Rahim et al. (2016) and Ulman et al. (2017) largely address acceptance through studies of usability, accessibility, and functionality. Other papers provide greater depth of insight. Jakku and Thorburn (2010) propose a novel conceptual framework for the development of decision support systems, which advocates participatory approaches and is theoretically grounded in context-specific, social learning frameworks (Pahl-Wostl and Hare, 2004), technological frames (Orlikowski and Gash, 1994), and boundary objects (Star and Griesemer, 1989). This approach provided the basis to co-create new decision support systems that were evaluated through qualitative interview studies. Mackrell et al. (2009) and Ravier et al. (2018) both report detailed studies that include qualitative methods and engaged deeply with representative users to understand the real-work use of technologies. Similarly, Ayerdi Gotor et al. (2020) provide a detailed study that considers the impact of diverse economic, social and environmental factors.

4.4. Mapping to constructs in the theoretical framework of acceptability

To better understand the degree to which studies address acceptance in a comprehensive manner, we mapped the data reported in the shortlisted papers to the seven constructs of the Theoretical Framework of Acceptability (TFA). This mapping allowed us to identify which constructs are commonly address and which have received less attention. In the analysis presented below, it is important to note that the focus is on identifying whether a construct has been addresses. The degree to which constructs acted as barriers or facilitators to technology acceptance is not assessed, as the data in the papers did not facilitate confident analysis at this level.

As shown in Table 7 no paper addressed all seven constructs of the TFA. Intervention/System Coherence (the degree to which the user understands the technology and it's working) was captured most often, in 15 of the 16 studies (94 %). This was followed by Perceived Effectiveness (the degree to which the users perceive the intervention as deriving anticipated results) and Self Efficacy (the degree to which the users are confident enough to make the necessary behaviour changes required by the system) which were both addresses in 11 studies (64 %). Affective Attitude (how users feel about the system) was addressed in 8 studies (50 %).

The remaining constructs were captured in a minority of studies. Burden (the perceived amount of effort needed by the user to use the intervention) and Ethicality (the degree to which the intervention blends in with the user's value system) which were captured in 5 (31 %) and 4 (25 %) studies respectively. Finally, Opportunity Costs (the consideration of what must be relinquished by the users to use the system) was captured in least number of studies, only 2 (12.5 %) of the shortlisted studies.

The primary aim in Table 7 was to identity the constructs which have received frequent attention and those addressed less often. We are reluctant to over interpret these findings, however, it does appear that constructs which are more functional, and more directly associated to farming output, (e.g., effectiveness) have received greater attention. Similarly, constructs traditionally associated with the ease of use of a system (e.g., coherence, efficacy) were also addressed by many shortlisted studies. In contrast constructs more closely associated with challenges introduced by new technology (e.g., burden, opportunity cost) or

Table 7
Mapping of seven constructs of the Theoretical Framework of Acceptability to the shortlisted articles.
AA - Affective attitude, BD - Burden, ET - Ethicality, IC - Intervention coherence, OC - Opportunity costs, PE - Perceived Effectiveness & SE - Self Efficacy.

Authors	AA	BD	ET	IC	OC	PE	SE
Jakku and Thorburn (2010)	X		X	X		X	
Li et al. (2020)					X	X	X
Iskandar et al. (2018)	X			X		X	X
Mackrell et al. (2009)		X		X			X
Sayruamyat and Nadee (2020)	X			X		X	
Ravier et al. (2018)		X		X			X
Souza et al. (2019)		X		X			X
del Águila et al. (2015)				X			X
Rahim et al. (2016)	X	X		X			
Caffaro et al. (2020)			X	X		X	
Jain et al. (2018)	X		X	X		X	X
Mir and Padma (2020)	X			X		X	X
Ayerdi Gotor et al. (2020)			X	X		X	X
Ulman et al. (2017)	X			X	X	X	
Michels et al. (2020a)		X		X		X	X
Mercurio and Hernandez (2020)	X			X		X	X

to the value systems of technology users (e.g., ethicality) have received less attention. This points to gaps that should be addressed in future research. Models like the TFA emphasise that rigorous examination across diverse constructs is necessary to better understand and support acceptance.

5. Discussion

The barriers and facilitators to technology acceptance identified in this review have key practical implications for the development and acceptance of smart agricultural technologies. Increased knowledge is a commonly cited facilitator, demonstrating the importance of adequate information, resources, and training materials. Information that is personalised and localized further supports acceptance. There is also significant overlap across the barriers and facilitators. For example, effective support for training is a facilitator, whereas lack of training and support is a barrier. A positive impact on productivity and resources (both time and cost) was a commonly identified facilitator, whereas increased infrastructure costs and increased burden reduced acceptance. New technologies may not be compatible with traditional technologies and hardware on the farms. In addition, the location of farms may be remote, creating challenges in regard to modernization and availability of digital infrastructure. While it is important that studies of acceptance go beyond considerations of usability, usability was clearly a key factor in acceptance. Systems that were overly complex or difficult to use were less likely to be accepted, whereas familiarity, reliability and market readiness facilitated acceptance. To be accepted in real-world use technology needs to directly address real world needs. Technologies that make substantial promises but then underdelivers, or which support trivial tasks, are less likely to facilitate acceptance. As noted above future research should also place greater emphasis on understanding the burden and costs associated with smart agriculture and on developing systems that respond to the values systems of the agricultural community.

The shortlisted studies used a range of models and methods to investigate technology acceptance. The TAM and its extended models were the most common approach. This is perhaps unsurprising given the widespread use of the model in other domains. In other shortlisted studies, particularly qualitative studies, the authors developed customized questionnaires and interviews to investigate technology acceptance. Interestingly, there was very limited use of mixed methods approaches combining qualitative and quantitative analysis. Going forward, greater use of mixed methods has the potential to generate deeper insights on technology acceptance, e.g., by using targeted qualitative methods to further investigate and explain quantitative findings. Aside from the TAM (which itself has not been formally validated in the smart agriculture space) most of the methods applied have not been formally validated, with researchers adopting their own methods to assess technology acceptance, based to their specific interests and needs. In some cases this led to a very narrow interpretation of acceptance, focused around usability and accessibility. As it stands, the absence of validated methods to address technology acceptance in the context of crop farming represents a key gap and goal for future research. Of the papers shortlisted in this review, two in particular provide valuable starting points for this work. Where quantitative and statistical methods are preferred, the Integrated Technology Acceptance Model proposed by Mir and Padma (2020) is promising. It is specific to agricultural decision support systems and takes a wide view of acceptance addressing the impact of technical, human, and organizational factors. However, as acknowledged by the authors, further research is required to validate this model. If a more qualitative perspective is required, the framework of Jakku and Thorburn (2010), which encourages participatory approaches, provides a strong theoretical grounding (e.g., in social learning and technology frames). Based on the analysis in Table 7, however, we would argue that further work is needed to address a greater of a breath of constructs related to technology acceptance.

In this paper we specifically applied the TFA, and we argue that this framework can also provide a valuable starting point to studying technology acceptance, not just in crop farming, but in smart agriculture more generally. It is user-centred and encourages the use of both quantitative and qualitative methods (i.e., a mixed methods approach). It supports the rigorous investigation of technology acceptance, based on seven empirically derived and wide-ranging constructs. Given that it was developed in the health domain, it is unsurprising given that TFA has not been applied in smart agriculture to date. Domain specific adaptation and validation will be required but, given the societal and economic importance of agriculture, this will be a worthwhile undertaking and would help to support a more rigorous and comprehensive study of technology acceptance. The results of our review show that the Intervention/System Coherence, Perceived Effectiveness and Self Efficacy constructs within the TFA were investigated in many studies. Inferred from our analysis of facilitators and barriers, this could imply that study designers and participants cared most about understanding the workings and implementation of the systems, how effective they could be, and how confident participants are in their ability to use the system. However, it most likely also reflects that these issues are more typically addressed studies of technology adoption. Affective Attitude was investigated by a smaller number of studies, while Burden, Ethicality and Opportunity Costs were addressed in few studies. These are crucial constructs that could determine the level of technology acceptance, as they are closely linked to end-users, their values and experiences. Also addressing these constructs will ensure that studies of acceptance address not just the benefits of technology, but also the burden and cost, both financial and non-financial.

One of the critiques made of the TAM is that it is overly focused on individual interactions with technology and does not sufficiently address broader the contextual and societal aspects of acceptance. In regard to social factors, this critique can also be made of the TFA (although we would argue the critique is less justified). As noted above, Jakku and Thorburn (2010) propose a framework that has a strong theoretical grounding in the social learning theories and social knowledge construction, which can help with address this limitation. Several papers in this review clearly demonstrate the importance on social factors. They emphasise the value of local knowledge and find that informal, community knowledge and links to farming associations have greater impact on attitudes toward technology than formal information sources, such as technology developers. More broadly, it will be beneficial for future studies of acceptance in smart agriculture to engage more deeply with the impact that context of use has on acceptance, considering for example individual and society factors or the impact that geographical factors have on the opportunities, costs and values systems of technology users.

6. Limitations

This review article has focused specifically on decision support systems in crop farming. As such it has not considered acceptance of broader technology in agriculture. Our focus enabled us to manage the overall scope of the review, but we argue the lessons learned also have relevance to other areas within smart agriculture, as decision support systems incorporate key elements of smart agriculture, including the use of rich data and machine learning to support day-to-day decision making.

This review followed PRISMA guidelines for systematic reviews with predefined search terms followed by screening using pre-defined inclusion and exclusion criteria. Screening and analysis were conducted jointly by two authors and disagreements were resolved through discussion. We argue these methods helped to reduce bias. However the possibility of subjective judgement in shortlisting articles and analysing the findings is acknowledged. In addition, the evaluation methods used in the research articles were different and samples were heterogeneous. The data in these studies were indicative of agricultural sample populations from different countries in specific regions. Additionally, the mapping of the shortlisted articles to the Theoretical Framework for Acceptability is the authors representation from the literature analysis.

Our decision to apply the PRISMA guidelines was based on its maturity and widespread use across different research fields. However, we acknowledge critiques and limitations of PRISMA identified by researcher in fields of conservation and environmental sciences (Haddaway et al., 2018).

7. Conclusions

This review has identified barriers and facilitators to technology acceptance. It has also considered the degree to which prior literature applied theoretical models and address acceptance in a rigorously and broadly defined manner. We have focuses on prediction and decision support systems in crop production. Our analysis shows that constructs including intervention coherence and perceived effectiveness have been frequently addressed. Other factors critical to acceptance, such as opportunity costs, burden and ethicality have received less attention. One key area for future work for in this area is the development of validated models or instruments, which can be used to investigate technology acceptance in crop farming. The formulation of such a model or instrument (e.g., a validated survey technique) would contribute to filling the gap that exists in the present methods of technology acceptance evaluations in this domain, and ultimately to greater societal impact.

Credit authorship contribution statement

RJT and DC contributed to the conception and design of the systematic literature review. RJT led the systematic screening process and data extraction. DC re-examined (screening by title and abstract) 5 % of the articles for all the databases and all the 63 articles in the second phase of screening. RJT was the lead author on the initial version of the manuscript. DC assisted in writing the initial manuscript and led the revisions of the final paper. DC and GOH proofread all drafts and contributed to the final text.

Declaration of competing interest

Not applicable.

Data availability

Limited data is available as most of the searches and filtering was done using the online databases functionalities. All the search keywords and queries are listed in the manuscript for reference.

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