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Digital agriculture technology adoption in low and middle-income countries—a review of contemporary literature

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The use of digital technology in low- and middle-income countries (LMICs) is shaped by multiple factors that can enable or hinder adoption. Understanding these factors is crucial, as LMICs face many constraints that limit the benefits of digital innovation. Therefore, this paper thoroughly evaluates the literature to identify the key determinants influencing the adoption of digital agriculture technologies in LMICs. A total of 30 relevant publications, dated between 2019 and May 2025, were retrieved from the academic databases Google Scholar, Scopus, and Web of Science through a systematic search and analysis approach with clearly defined inclusion criteria to ensure relevance and comparability. This study highlights that socioeconomics, agro-ecological, technological, institutional, situational, social, and behavioral factors are the most frequently discussed influences on digital agriculture technology adoption. Nonetheless, only a few studies have examined all of the components of the complex adoption process, and the majority were only concerned with assessing the impact of a single factor. The findings suggest that these factors positively influence the adoption of digital agriculture technologies, but their effects vary across contexts. The study recommends that policymakers, practitioners, and development agencies adopt integrated strategies that address multiple barriers simultaneously to enhance the uptake and sustained use of digital agriculture technologies.

KEYWORDS

digital agriculture technology, elements, low and middle-income countries, scoping review, literature

1 Introduction

Agriculture is the practice of nurturing land, reaping yields, and raising animals for different aims, including food production, fiber, medicinal plants, and other products used to sustain and advance human life. As of 2022, approximately 892 million people worldwide rely largely on agriculture and forestry for income (FAO, 2022), and farmers rapidly adopt digital agriculture technologies to enhance production (Duncan et al., 2021). The finances of many low and middle-income nations (LMICs) are led by agriculture, so advancing the agricultural sector is key to economic growth and prosperity. The development and uptake of new technologies have shaped the farm production system throughout history. Digital technologies, for instance, robotics, big data, the Internet of Things (IoT), sensors, augmented reality, 3D printing, artificial intelligence, ubiquitous connectivity, machine learning, integration systems, digital twins, and blockchain, among others, are in use by farmers worldwide (Klerkx and

Rose, 2020). Digital technology profoundly transforms daily life, dynamic agricultural processes, related food, fiber, and bioenergy supply chains, structures, and preparatory revolution symbols (Choi et al., 2022). Integrating numerous agricultural technologies sparks the fourth agricultural revolution, also known as agriculture 4.0. (Figure 1; Cui and Wang, 2023).

Digitalization in agriculture is likely to deliver technical optimization of agricultural production ways, value chains, and food systems (Barrett and Rose, 2022; Lajoie-O'malleya and Van Der Burgs, 2020). Researchers have focused on discovering how digital agriculture links to economic, environmental, and social consequences (Lajoie-O'malleya and Van Der Burgs, 2020), particularly how technologies have transformed farmers' values, practices, and identities (Borman et al., 2022; Parlasca et al., 2022). Moreover, mutual interests such as food provenance and traceability, animal well-being in livestock businesses (Alshehri, 2023), and the ecological impact of various farming practices have been highlighted (Tullo et al., 2019). Despite this, past literature also identifies numerous potential opportunities for digital agriculture technology adoption that have not yet been met in LMICs. These opportunities include improving market access and financial inclusion by connecting farmers to markets, credit, and insurance services; improving climate resilience and precision agriculture through AI-based weather forecasting and IoT-enabled local monitoring systems (Tyagi and Tiwari, 2025); increasing supply chain transparency and efficiency through blockchain and smart contracts to ensure fair compensation and reduce losses; and providing timely extension services and agronomic advisory support (Khanday, 2025). The progress of digital technology in the agriculture sector is very gradual. Various essential elements must be in place before digital agriculture can recognize its full potential, such as equity and equality of access to technology, mobile networks, and electricity (Liu et al., 2021). For instance, in Sub-Saharan Africa, barely 47 percent of the population has access to electricity, and mobile connectivity has still to reach critical mass in many regions (Kudama et al., 2021). In LMICs like Sub-Saharan Africa, the Pacific, and East and Southeast Asia, many farmers have been working on small farms, and their livelihood depends on small-scale agricultural activities. These countries face challenges in adopting and accessing agricultural technologies (Hoang and Tran, 2023). As a result, educating farmers about new prospects and offering access to agricultural technology adoption are key tactics for increasing agrarian output efficiency and farmers' small-scale livelihoods.

According to World Bank definitions (Data: World Bank Country and Lending Groups, 2019), LMICs are those with an annual gross national income per capita of <US$3,995, whereas upper-middle-income and high-income countries combined have an annual gross national income per capita of ≥US$3,995 (Papri et al., 2021). In a real setting in LMICs, agriculture is hindered by limitations in adopting digital technology, such as infrastructure, lack of knowledge and understanding, inaccessibility, high illiteracy rate, digital literacy, lack of transparency, socio-demographic, and institutional characteristics (Ruzzante et al., 2021; Porciello et al., 2022). These hurdles have made it more difficult to use digital technologies and slowed the progress of smart agriculture. Recognizing the significance and effectiveness of digital technology adoption in agriculture, alongside identifying current challenges in its execution, is essential. These concerns must be addressed head-on for digital agriculture to realize its potential fully and significantly contribute to the sector's sustainable farming practices, food security, and economic development. Understanding the components of digital technology adoption that might reinforce existing outcomes and situations, alleviate stream issues, and develop digital agriculture for more sustainability is increasingly important.

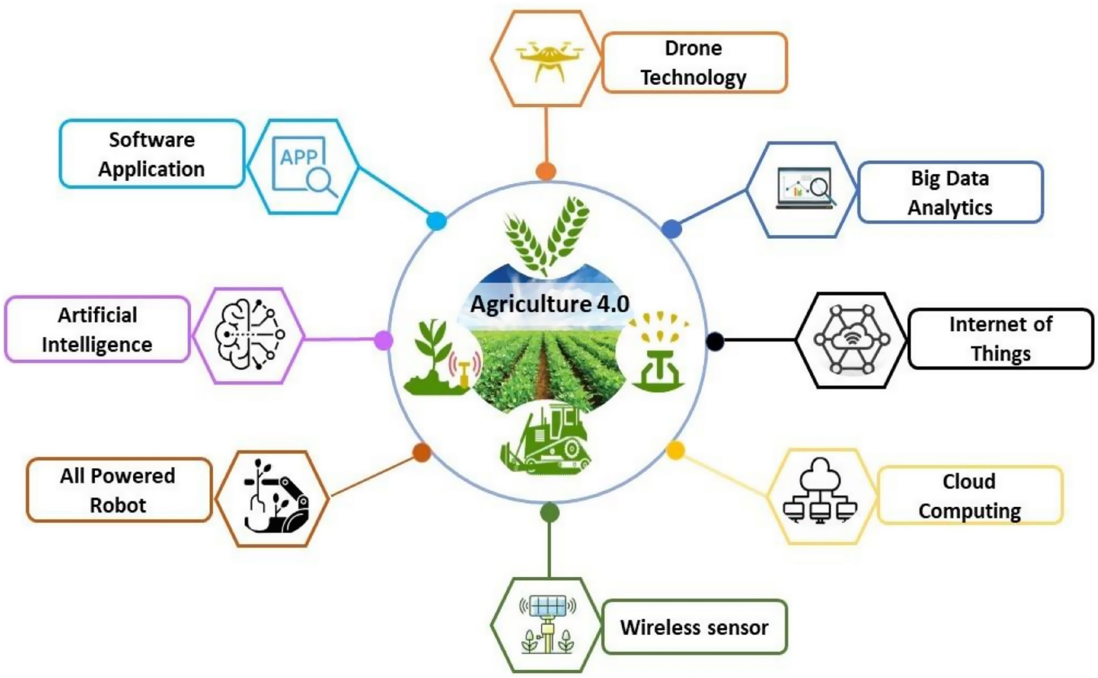

FIGURE 1
The conceptual structure of "Agriculture 4.0" adopted by the previous study (Cui and Wang, 2023).

The present study highlights a scoping review of factors affecting the adoption of digital agriculture in LMICs, improving the literature on digital agriculture in two important ways: Initially, we examine and compile the research on determinants influencing digital technology adoption, which helps illuminate the significance of these technologies in the agricultural sector. Second, we propose areas for further exploration: (1) investigating specific factors that influence the adoption of digital agriculture, (2) examining the effects of key components highlighted in previous studies, and (3) studying the challenges in adopting digital agricultural technologies, along with recommending potential solutions.

2 Methods

The present work is a scoping review to emphasize the scope and factors affecting digital agriculture technology adoption in LMICs. The scoping review is considered to thematically describe the scope, extent, and description of prevailing evidence through a five-step procedure proposed by Arksey and O'Malley (2005). First, we recognize the study question; next, we classify applicable and relevant research studies through a structured search strategy; screen them based on predefined inclusion and exclusion criteria to ensure relevance and quality, extract key information by using a standardized data-charting form, and finally, findings were collated, summarized, and analyzed thematically. The study selection process was conducted per the PRISMA 2020 guidelines, and the results are presented in the PRISMA 2020 flow diagram.

2.1 Search approach and study selection

We searched academic databases Google Scholar, Scopus, and the ISI Web of Science for synonyms and keywords related to adopting digital agriculture technologies in LMICs. The search terms concentrated on elements promoting the adoption of digital agriculture technology. These sources are considered significant because case studies, reports, and other non-academic publications highlight the components influencing the adoption of digital technology. The literature search was conducted in May 2025 from the ISI Web of Science, Scopus, and Google Scholar databases for sample collection. The analysis was initiated from the year 2019 to capture recent and relevant developments in the field, as the majority of significant contributions on this topic have emerged within the last 5–6 years. Data for 2019 was selected because this period represents a stage when these technologies had begun to achieve broader dissemination and adoption across several LMICs, thereby making it a particularly relevant and representative timeframe for analysis (Amoussouhoui et al., 2024).

The following criteria were used for the search: (a) topics: "factors" and "digital agriculture adoption," (b) periods: from 2019 to 2025, (c) filtering paper type: as "Article." With the same strategy, we discovered articles by searching "determinants influencing/promoting digital agriculture adoption" and "components affecting digital agriculture adoption in LMICs." Furthermore, we used a search string method such as ("digital agriculture adoption") AND ("digital technology adoption" OR "Agriculture 4.0 adoption" OR "Industry 4.0 adoption" OR "smart farming adoption" OR "precision agriculture adoption"). Figure 2 shows the search and screening steps of the article selection process according to the PRISMA 2020 strategies. After the initial screening, 15,184 records were identified. Reading each paper's abstracts and titles helped with the next screening phase. After narrowing the research topic and restricting the language to English only, 6,661 records remained. Removing publications like books, editorials, and seminar summaries that were not relevant reduced the total to 1,433. In the final step, after full-text screening, only 30 of the 1,433 papers were found to be directly relevant to the review's subject and were selected for further analysis.

2.2 Inclusion and exclusion criteria

All research studies address components affecting the adoption of digital agriculture technology. These components are socio-economic factors, institutional determinants, and societal and environmental elements on adopting digital technology; other irrelevant factors were excluded, such as the studied technologies that are not on-farm digital technologies. All the included studies focused on original data from the target population(s) and geographies such as LMICs. Studies that identified digital agriculture technology without doing intervention testing with our target population were omitted. Original research articles and English-written studies were added; non-original and non-available in full-text articles were excluded. Non-English language publications were not investigated, which could have resulted in bias in the literature.

3 Results

3.1 Evaluated papers

Basic information about the 30 selected research publications is available in Table 1. These studies incorporate the general digital agriculture field to specific digital technologies such as IoT traceability technology, smart pesticide technology, drones or unmanned aerial vehicles technology, robotics, telecommunication systems, mobile apps, remote sensing, blockchain, artificial intelligence, and other relevant technologies. Regression modeling, technology acceptance modeling, and structural equation modeling are common quantitative techniques that use data acquired through surveys or interviews with farmers. The geographical areas are mostly the main agricultural production zones across LMICs, and the sample sizes varied from 112 to 1,985. The results of these investigations serve as the empirical foundation for this review evaluation.

3.2 Identification and classifications of elements

Several critical factors emerged as significant determinants influencing the adoption of digital agriculture technologies in the studies reviewed. Table 2 specifies these components into six key types (i.e., socio-economic, agri-ecological, technological, situational, institutional, psychological, social, and behavioral). The ensuing section provides a full explanation of each component.

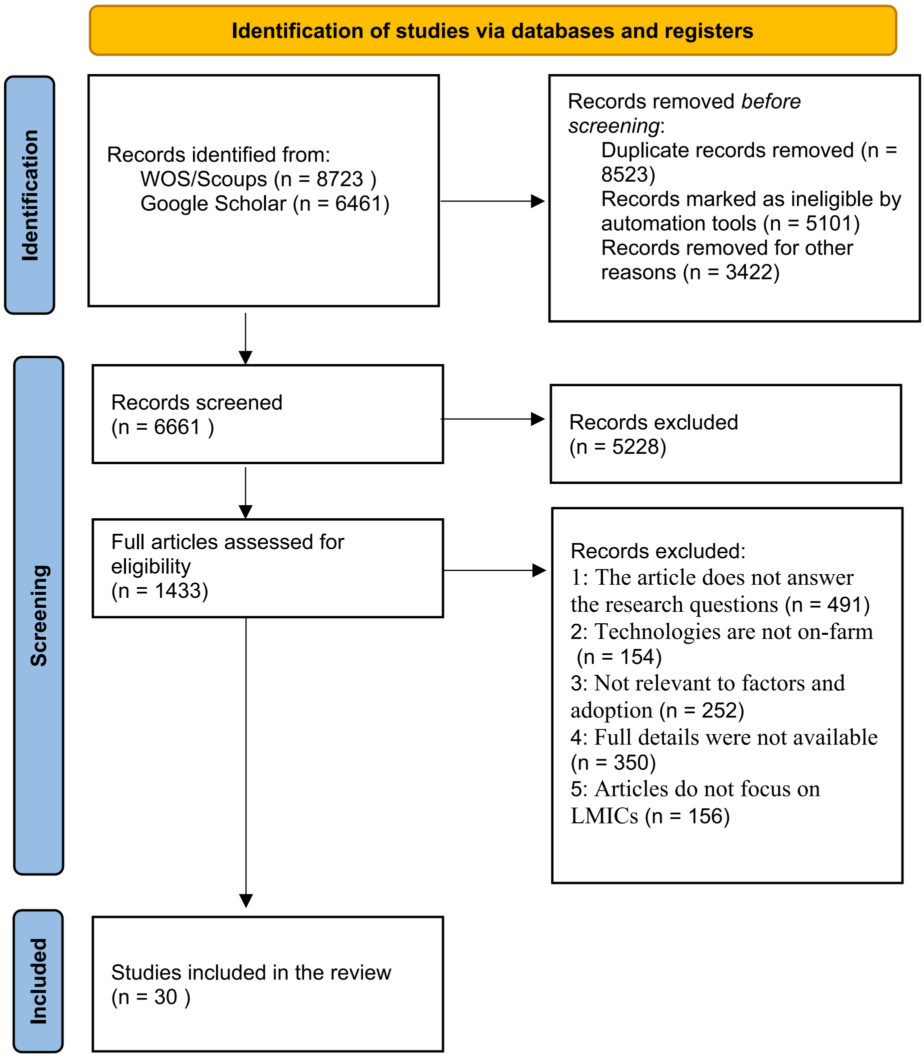

FIGURE 2
Data screening process using the PRISMA (2020) flow diagram.

3.2.1 Socio-economic components

Socioeconomic elements are the personal information of farmers who have adopted digital agricultural technologies. Several agricultural technologies need a large amount of human capital (Tey et al., 2024). Farmers' capabilities and knowledge affect their decision to adopt digital agriculture. Numerous studies highlighted socioeconomic components in analytic simulations as predictor constructs (Hoang and Tran, 2023; Hebsale Mallappa and Pathak, 2023; Zheng et al., 2019; Thar et al., 2021; Zakaria et al., 2020; Kitole et al., 2023). Noteworthy socioeconomic elements in the selected articles are age (Wang et al., 2024; Yatribi, 2020), gender (Nyagango et al., 2023), education (Hebsale Mallappa and Pathak, 2023), farming experience (Nazu et al., 2021), agricultural income (Zheng et al., 2019), and household or off-farm income (Miine et al., 2023). These articles reveal that young farmers are more technologically oriented and willing to adopt digital agriculture technology than older people (Thar et al., 2021; Bontsa et al., 2023). The influence of gender on adopting digital agriculture technology reveals an inconsistency in preferences. Men farmers use agricultural technologies more, and female farmers are less likely to adopt them (Nyagango et al., 2023; Krell et al., 2021). Adopting digital agricultural technology is strongly linked to farmer education because these tools necessitate knowledge-based skills and understanding (Hebsale Mallappa and Pathak, 2023; Nyagango et al., 2023; Krell et al., 2021). Similarly, farming experience positively influences the adoption of digital agricultural technologies (Zakaria et al., 2020; Nazu et al., 2021). This shows that experienced farmers are more willing to adopt cutting-edge and sophisticated technologies since they require less assistance from others throughout the implementation process. Despite opposing views about farm and non-farm income, studies have shown that the acceptance of digital agricultural equipment is unaffected by either source of income (Thar et al., 2021). In addition, research discovered that the higher the percentage of farming income, the larger the tendency to adopt technology (Zheng et al., 2019), and high household income is more effective in predicting farmers' adoption of digital agriculture (Hebsale Mallappa and Pathak, 2023; Miine et al., 2023).

3.2.2 Agro-ecological components

Agroecology, recognized as agricultural ecology, is a farming method that considers ecological elements. It integrates ecological

TABLE 1 Details of reviewed articles.

Authors and publication time	Analytic technique	Reviewed technologies	Study areas	Farmers type	Sample size	No. of parameters	Model of significance
Zakaria et al. (2020)	Multivariate Probit and Poisson regression models	Climate-Smart Agricultural Technology	Northern Ghana	Rice farmers	543	15	Sig.
Li et al. (2020)	Structural Equation modeling	Precision agriculture technologies	China	Crop farmers	456	08	Sig.
Ronaghi and Forouharfar (2020)	Structural Equation model	Internet of things (IoT)	Middle Eastern country Iran	General farmers	392	07	Sig.
Zheng et al. (2019)	Technology acceptance model (TAM)	Aerial Pesticide Application	Jilin Province, China	Rural farmers	897	10	Sig.
Kante et al. (2019)	Partial least squares structural equation modeling technique	Information and communication technologies (ICTs)	Sikasso, Mali	Small-scale cereal farmers	300	11	Sig.
Krell et al. (2021)	Generalized Linear Model and Generalized Linear Mixed Effects Model	Mobile phone service	Central Kenya	Rural farmers	577	12	Sig.
Hoang and Tran (2023)	Binary Logistic regression	Varies digital technologies	Vietnam	Smallholder farmers	202	13	Sig.
Meng et al. (2023)	Double-hurdle model	Precision Pesticide Technologies	China	Apple farmers	545	18	Sig.
Yoon et al. (2020)	Structural Equation modeling	Smart farms adoption	Korea	Farmers and members	232	12	Sig.
Thar et al. (2021)	Probit model	Mobile app	Myanmar	Farmers	600	08	Sig.
Hebsale Mallappa and Pathak (2023)	Path analysis	Climate smart agriculture technologies	India	Farmers	240	16	Sig.
Miine et al. (2023)	Multivariate probit and Heckpoisson regression models	Adoption of digital agricultural services	Ghana	Smallholder farmers	1,199	12	Sig.
Kitole et al. (2023)	Double-hurdle model	Agricultural digitalization	Tanzania	Smallholder farmers	400	15	Sig.
Khan et al. (2020)	Bivariate probit Regression Model	Mobile based farm advisory services	Pakistan	Small household farmers	180	11	Sig.
Akudugu et al. (2023)	Multivariate probit	Digital agricultural production services	Ghana	Household farmers	1,294	14	Sig.
Diaz et al. (2021)	Extended Technology Acceptance Model	Mobile app	Philippines	Bamboos farmers	112	12	Sig.
Zheng et al. (2022)	Binary probit regression Model	Internet use	China (14 Provinces)	Smallholder farmers	1,449	21	Sig.
Ulhaq et al. (2022)	Technology acceptance Model	ICT	Vietnam's provinces	Shrimp farmers	184	12	Sig.
Nazu et al. (2021)	Tobit Model	Wheat management practice	Bangladesh	Wheat farmers	320	13	Sig.
Khan et al. (2022)	Bivariate probit Model	Mobile internet	Pakistan	Wheat farmers	628	11	Sig.
Kabirigi et al. (2023)	Logistic regression model	Smart Mobile phone	Rwanda	Banana farmers	690	04	Sig.
Benimana et al. (2021)	Multivariate Probit Model	Maize storage technology, i.e., Hermetic storage technology (HST)	Gatsibo District-Rwanda	Small household farmers	301	10	Sig.

(Continued)

TABLE 1 (Continued)

Authors and publication time	Analytic technique	Reviewed technologies	Study areas	Farmers type	Sample size	No. of parameters	Model of significance
Nyagango et al. (2023)	Binary logistic regression	Mobile Phone	Tanzania	Grape smallholder farmers	400	10	Sig.
Bontsa et al. (2023)	Tobit regression	Digital technology adoption	South Africa	Smallholder farmers	250	14	Sig.
Kumar et al. (2020)	Poisson regression method and seemingly unrelated regressions	Improved farm technologies adoption	Nepal	Household farmers	1985	39	Sig.
Wang et al. (2019)	Structural equation model	Agricultural information technology	China	Farmers	288	05	Sig.
Wang et al. (2024)	Binomial logistic regression models, and multiple linear regression models, and regression decomposition method	Farmers' grain production technology innovation	China	Farmers	1,046	14	Sig.
Savari et al. (2024)	Structural equation model	Climate Information Services	Iran	Farmers	390	07	Sig.
Sharma et al. (2025)	Structural equation model	FinTech adoption	India	Farmers	362	04	Sig.
Nguyen and Hoang (2025)	binary logistic regression model	Information and Communication Technologies (ICTs)	Vietnam	Farmers	217	10	Sig.

concepts into agricultural techniques to develop sustainable and resilient agricultural systems. The entire land area available for agricultural production is the farm size. Though this is a vital factor, the outcomes of the reviewed articles are ambiguous. For instance, cultivators with large land sizes are more likely to adopt digital agriculture (Hoang and Tran, 2023; Miine et al., 2023; Meng et al., 2023). Conversely, Zakaria et al. (2020) discovered that farmers with small farm sizes tend to adopt digital technologies, presuming that the associated expenses will be low. Moreover, Krell et al. (2021) it was found that farm size is not significantly related to adopting agricultural technology. Temperature, climate change, and rainfall influence the productivity and health of crops and livestock. Climate monitoring, modeling for prediction, and weather awareness tools improve agricultural output. Therefore, digital agriculture applications effectively track weather updates like rainfall and temperature, impacting adoption (Zakaria et al., 2020; Kumar et al., 2020). The selected studies have not thoroughly examined certain agroecological components, including crop diversity and rotation, soil health, water management, and pest and disease control.

3.2.3 Technological components

Digital agriculture technology adoption depends on data and equipment control, the need for technology, knowledge of new equipment, implementation cost, and information availability. Technology adoption is facilitated by characteristics that are compatible with work needs. When a technology's perceived capabilities and task requirements align, a perceived demand for it develops. Articles claim that farmers' adoption of agricultural technologies is positively influenced by their perceived need to use technology (Li et al., 2020). Furthermore, the degree to which a person comprehends that mechanical and technical infrastructures allow the use of technology and systems is known as facilitating conditions (Venkatesh et al., 2003). Ronaghi and Forouharfar (2020) discovered that conducive conditions motivate farmers to use digital agriculture instruments. This may eliminate hurdles that prevent farmers from embracing new technologies (Li et al., 2020). A farmer's awareness of new technologies encourages them to accept them (Zheng et al., 2019). Moreover, the low-cost instruments (Nyagango et al., 2023; Cucho-Padin et al., 2020) and digital communication methods (Meng et al., 2023; Kante et al., 2019) raise the smart farming. Rather, significant financial costs limit adoption (Yoon et al., 2020). Farmers are more willing to use technology and apps if they can get timely and cost-effective agricultural information over the Internet.

3.2.4 Institutional components

Understanding agricultural modernization requires institutions such as government agencies, cooperatives, commercial units, loan provider groups, and training facilities. Selected articles demonstrated that government backing and subsidies significantly improve farmers' readiness to adopt agricultural technologies (Yoon et al., 2020). Information and enhanced information-sharing opportunities, such as agri-researchers, service providers, and cooperative membership in farmer groups, lead to a growth in the usage of digital technologies (Hoang and Tran, 2023; Kitole et al., 2023; Krell et al., 2021; Meng

TABLE 2 Major components affecting the adoption of digital agriculture technologies.

Types of elements	Substantial parameters	Outcome (+/−)	Sources
Socio-economic elements	- Age - Gender - Education - Experience - Agriculture income - Household/off-farm income	+ +/− + + −/+ +/−	Bontsa et al. (2023), Krell et al. (2021), Nyagango et al. (2023), Hebsale Mallappa and Pathak (2023), Nazu et al. (2021), Zakaria et al. (2020), Zheng et al. (2019), Miine et al. (2023) and Thar et al. (2021)
Agro-ecological elements	- Farm size - Temperature - Climate change and rainfall	+ + +	Hoang and Tran (2023), Meng et al. (2023), Miine et al. (2023), Zakaria et al. (2020) and Kumar et al. (2020)
Technological elements	- Perceived need for technology characteristics - Facilitating condition - Understanding of new technology - Cost of technology - Access to information	+ + + +/− +	Li et al. (2020), Ronaghi and Forouharfar (2020), Cucho-Padin et al. (2020), Nyagango et al. (2023), Kante et al. (2019), Meng et al. (2023) and Yoon et al. (2020)
Institutional elements	- Government support - Access to financial credit - Access and participation to training - Access to agri-researcher and service providers - Membership in farming organizations/ cooperatives	+ + + + +	Yoon et al. (2020), Hoang and Tran (2023), Kitole et al. (2023), Krell et al. (2021), Meng et al. (2023), Zakaria et al. (2020), Miine et al. (2023), Kumar et al. (2020) and Benimana et al. (2021)
Situational elements	- Farm distance from market - Home-farm distance	+/− +/−	Kumar et al. (2020), Thar et al. (2021), Kitole et al. (2023) and Zakaria et al. (2020)
Social and behavioral elements	- Perceived risk - Perceived usefulness - Perceived ease of use - Performance expectancy - Effort expectancy - Social influence	+/− + + + + +/−	Hebsale Mallappa and Pathak (2023), Li et al. (2020), Bontsa et al. (2023), Diaz et al. (2021), Zheng et al. (2019), Ronaghi and Forouharfar (2020) and Kante et al. (2019)

et al., 2023). One of the factors that influences technology adoption is the availability of researchers (Zakaria et al., 2020). Farmers' involvement in cooperatives improves access to production knowledge and innovation (Kumar et al., 2020). Access to financial or credit services and training centers is positively related to the farmer's adoption of technologies (Zakaria et al., 2020; Miine et al., 2023; Meng et al., 2023; Benimana et al., 2021). These outcomes indicate that consistent government and cooperative support encourage farmers to adopt innovative farming methods.

3.2.5 Situational components

Farmers away from the market are likelier to use the digital application to get information. Farmers' adoption of new technologies is significantly impacted by the distance to the nearest marketing hub (Kumar et al., 2020). Farmers who reside far from marketplaces are less likely to use digital applications, as reported by Thar et al. (2021) market distance, which is negatively significant. Furthermore, studies showed that the distance from farm to market and home to farm has a detrimental impact on the extent of farmers' adoption of technologies (Zakaria et al., 2020; Kitole et al., 2023). The reason could be that smallholder farmers' farms are away from their homes, making it hard for extension agents to access markets. This leads to poor technology uptake.

3.2.6 Social and behavioral components

Implementing new digital technologies entails more than simply technical considerations. Participants' and stakeholders' attitudes, actions, and beliefs also influence it. For example, Hebsale Mallappa and Pathak (2023) discovered that farmers' perceived risk will likely impact their use of digital technologies in agriculture. One study found that perceived risks have a considerable detrimental impact on farmers' adoption of technologies (Li et al., 2020). Perceived ease of use indicates the ability to use relevant information and operating processes related to technology. Farmers are less inclined to adopt new technology they perceive to be tough to use. Perceived usefulness also pertains to how farmers consider that the technology will improve efficiency, production, and effectiveness. Farmers who believe the technology is advantageous are more likely to use it. Hence, the studies discover that the perceived ease of use (Bontsa et al., 2023) and perceived usefulness (Diaz et al., 2021) considerably drive the intention to adopt the technologies (Zheng et al., 2019). Performance expectancy is the extent to which an individual believes that employing technology helps him accomplish his tasks better. The level of perceived convenience in incorporating technology is called effort expectancy (Venkatesh et al., 2003). We discovered that performance and effort expectancy had a major influence on technology adoption (Ronaghi and Forouharfar, 2020). The term "social influence" refers to an individual's view of someone's notion about using technology and systems (Zhang et al., 2020). There are incompatible outcomes of social influence on the adoption; for instance, some studies highlight that the social influence elements positively influence the adoption of digital technologies (Hebsale Mallappa and Pathak, 2023; Ronaghi and Forouharfar, 2020; Kante et al., 2019; Diaz et al., 2021). Nevertheless, Li et al. (2020) it was revealed that social influence is insignificant when adopting technologies.

3.3 Challenges in the adoption of digital agricultural technology

In LMICs, the adoption of digital agriculture technologies has several challenges. Farmers in most nations are ignorant of digital technologies, possess inadequate training and expertise, and lack the knowledge to use them effectively. Training courses and ongoing support are critical for the successful deployment of technologies. Financing expenditures in digital technology is difficult for small-scale farmers with limited financial capabilities. The initial expense of acquiring and implementing digital agricultural tools is elevated. As a result, updating their processes while remaining sustainable is tough (Smidt and Jokonya, 2022). Many rural areas lack basic digital infrastructure, especially internet access, storage spaces, and electricity, which prevents the application of digital technology in agriculture (Rola-Rubzen et al., 2020). Farmers' concerns regarding the privacy and security of their agricultural data may serve as another obstacle to digital technology adoption. Many LMICs have a culture of uncertainty about novel solutions and technologies. As a result, conventional farming practices are deeply established, and many farmers avoid embracing new technologies for fear of losing their benefits (Ruzzante et al., 2021).

Furthermore, the lack of legislation supporting digital agriculture serves as a barrier to adoption. An insufficient regulatory framework can stymie the digital revolution's application in agriculture. Agriculture firms might be unable to prepare for and invest in the digital revolution if digital technology is not adequately regulated (Khanna and Kaur, 2023).

Despite this, the agricultural industry in LMICs can leverage digital technology to increase farm productivity and encourage environmentally friendly and sustainable farming practices. Nevertheless, these challenges require a collaborative effort from the public and private agricultural sectors, governments, educational institutions, technology developers, and societies.

4 Discussion

This review highlighted the determinants impacting the adoption of agricultural technologies in LMICs. This review found that adopting digital agriculture technologies results from multidimensional factors. It is positively related to (i) socioeconomic elements (young farmers, males, highly educated, experienced farmers and have a farm and off-farm income), (ii) agro-ecological elements (farm size, climate change, and rainfall), (iii) technological elements (perceived need for technology characteristics, facilitating condition, understanding of new technology, cost of technology, access to information), (iv) institutional elements (government support, access to financial credit, access and participation to training, access to agri-researcher and service providers, membership in farming organizations/cooperatives), and (v) Situational components (farm distance from market, and home-farm distance), (vi) social and behavioral elements (perceived risk, perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, social influence).

It is important to emphasize that characteristics of farmers and farms, particularly education, experience, income level, and farm size, are documented as generally stable components and are rarely addressed as critical elements in research performed in developed nations (Olum et al., 2020). Studies seldom consider socioeconomic characteristics because they are consistent throughout developed countries (Dibbern et al., 2025; Oli et al., 2025). Nevertheless, the present study displays that these determinants are important for farmers' adoption of agricultural technologies in LMICs. The agriculture sector in LMICs is distinguished by small-scale farming and a noteworthy assortment. The progressive economic development and execution of rural rehabilitation initiatives have resulted in a tremendous increase in the farming scale. During the swift shifts in rural setups and farming workforce systems, it is still vital to consider socioeconomic elements for empirical studies. In this article, socioeconomic factors, considering age, the older farmers tend to be conservative and reluctant to change and adopt technologies due to risk aversion. Compared to older young farmers, they are more open to innovations and more likely to adopt new technologies (Fragomeli et al., 2024). The adoption rate increases with the farmer's education level, especially if technology is advanced, and learning is necessary for its use. The influence of gender on adopting new technologies remains unclear in most cases. According to agricultural and non-agricultural income, the higher the farm income, the more likely the farmer is to adopt new technologies. These findings align with a previous research study (Yatribi, 2020).

With all six groups of components, situational and agroecological are the least determined in the reviewed studies. Land size, temperature, climate change, rainfall, and farm distance from the market and home are the factors studied in this group. In developed nations, many articles have uncovered other determinants like irrigation water availability, soil quality, crop yields, and climate shocks, which are effective in adopting digital technologies (Khanna et al., 2022; Moysiadis et al., 2021). Moreover, Farmers value the agricultural revolution and are adaptable to natural conditions and climate change (Khanna and Kaur, 2023). Considering these factors in this study may lead to a tilted acceptance of technology adoption.

Most farmers' decisions to adopt digital technologies are typically driven by greater profitability and revenue. The cost of these technologies often acts as a barrier, negatively influencing farmers' adoption. Nevertheless, a few institutional components, like government support or incentives, the availability of financial credit facilities, and reliable service providers, can motivate farmers to adopt agricultural technologies, notwithstanding their price (Dibbern et al., 2024). Institutional components ultimately increase the perception of farmers and technology adoption rates. The literature indicates that the intensification of profit and the role of social and behavioral elements induce the adoption of technologies. The outcome proposes that the perceived risk, usefulness, and ease of adopting modern innovations are important in decision-making (Cui and Wang, 2023). Institutional and behavioral components are very flexible; therefore, intervention can increase the likelihood of agricultural technology adoption. For example, raising awareness and providing information about environmental degradation and climate change might help people comprehend sustainability better. Most farmers accept contemporary agricultural methods due to financial and technical help, regardless of their perceived profitability (Cui and Wang, 2023).

This review exhibits opportunities to transform the concept into reality as digital agriculture gradually emerges from the hype. Digital technological competencies are rapidly evolving (Abbasi et al., 2022), and their prices will likely fall. Though this review study offers useful information on these new technologies, more comprehensive research is required to bridge the gap between technological innovation and its applications. That work can guide the expansion of digital agriculture for private and societal gains. Future research should investigate barriers unique to specific LMICs, such as cultural, regulatory, and infrastructure-related factors, to better understand how localized challenges impact digital agricultural technology adoption.

The findings have several significant implications. To encourage the adoption of digital agricultural technologies, the government should develop region-specific plans to solve specific challenges, such as legislative constraints in Southeast Asia and infrastructure limitations in Sub-Saharan Africa. Investing in farmer training and capacity building ensures these instruments are used effectively. Furthermore, to promote accessibility and adoption, digital solutions should be tailored to local language, literacy levels, and cultural norms. While boosting access to markets, information, and financial services can help reduce rural poverty and close the digital divide, particularly in low-income communities, strengthening public-private partnerships can accelerate innovation, cut costs, and enhance scalability. Additionally, policymakers, technology developers, and other stakeholders can work together to establish a climate conducive to the successful adoption of digital agriculture technologies, resulting in greater agricultural production, sustainability, and resilience.

5 Conclusion

This review article provides an overview of components influencing the adoption of digital agriculture technology in LMICs. This exploratory review synthesizes evidence from previous studies on the factors influencing digital agricultural technology adoption and underscores that multi-dimensional considerations shape farmers' adoption decisions. The adoption of digital agriculture technology is influenced by various technological, economic, social, situational, and institutional factors. For digital technologies to be successfully implemented and widely used in agriculture, it is essential to recognize these elements. This review found six components affecting the adoption of digital agricultural technologies. These important elements are socioeconomics, agroecological, institutional, technological, situational, social, and behavioral. Certain research studies have identified multiple factors related to the adoption of digital technologies, and most of them cannot be determined solely by assessing the impact of a single factor. This article combines previous information to recognize areas that require further research and policy development. This approach allows researchers, policymakers, and practitioners to receive unique insights about how to increase technology adoption rates. Accelerating digital technology adoption in rural areas needs collaboration between individuals, governments, technology providers, and extension agents. Policies can help ancillary farmers gain better access to information and services, improve their knowledge and proficiency, and reduce risk perception.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

Author contributions

FM: Formal analysis, Data curation, Methodology, Writing – review & editing, Conceptualization, Investigation, Writing – original draft. LW: Resources, Writing – review & editing, Supervision, Writing – original draft, Funding acquisition. MS: Data curation, Writing – review & editing, Conceptualization. XL: Writing – review & editing, Supervision, Validation, Funding acquisition. GQ: Writing – review & editing, Methodology, Validation, Resources, Visualization.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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