

## Review

# Factors Affecting the Adoption of Digital Technology by Farmers in China: A Systematic Literature Review

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**Abstract:** Increasing pressure for food security and environmental sustainability has highlighted the need to switch from conventional agricultural methods to advanced agricultural practices. Digital agricultural technologies are considered promising solutions for sustainable intensification of food production and environmental protection. Despite significant promotional efforts initiated in recent years in China, the adoption rate remains low. The objective of this study is to gain insight into the factors affecting the adoption of on-farm digital technologies in China using a systematic review approach that analyzes 10 relevant studies. Data regarding methodological aspects and results are extracted. We identify 19 key adoption drivers that are related to socioeconomic, agroecological, technological, institutional, psychological, and behavioral factors. There is a predominance of ex-ante studies that use stated preference methods. We conclude with a discussion of the design of policy incentives to induce the adoption of digital technologies. Additionally, the review points to the limitations of existing research and suggests approaches that can be adopted for future investigations. This review provides meaningful implications for the development of future efforts to promote digital transformation for sustainable agriculture in China.

**Keywords:** digital agricultural technology; technology adoption; sustainable agriculture; systematic review; factors of adoption



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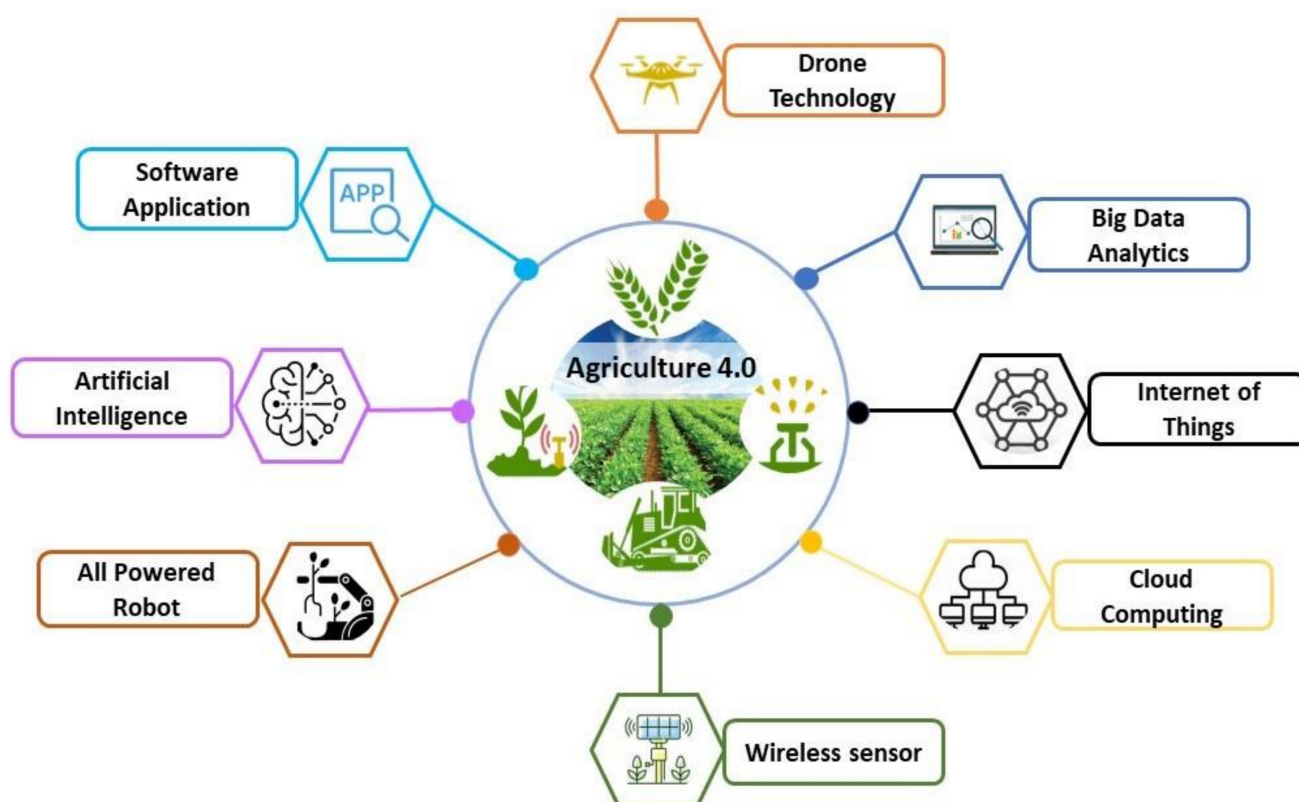
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## 1. Introduction

Certain eras in agricultural development were marked by significant technological changes that were dubbed “agricultural revolutions”. Digitalization, the sociotechnical process of implementing digital advancements, is expected to lead to the next agricultural revolution. Within agricultural production systems, various terms have emerged to indicate different forms of digitalization, including precision agriculture, digital agriculture, and smart farming. While there is no consistent term representing such a revolution, it is commonly characterized by a fusion of emerging digital technologies such as the Internet of Things, big data, robotics, remote sensors, and artificial intelligence. The integration of these technologies in agriculture is sparking the fourth agricultural revolution, referred to as agriculture 4.0. (Figure 1). The current agricultural system is largely able to feed the world with more cheap food calories but at the expense of increased greenhouse gas emissions and a destroyed environment. Addressing the challenge of sustainable development involves a revolutionary change in current farming practices. The advent of digital technologies has the potential to enhance the efficiency of input usage, increase crop productivity, and reduce environmental harm, thereby benefiting both farmers and consumers [1,2]. The best hope for achieving sustainable agricultural development lies in the innovative digital technologies to enhance agricultural productivity while balancing economic, environmental, and social outcomes associated with agricultural systems [3]. However, the adoption of digital tools by farmers, especially smallholder farmers in developing countries, is slow and low. This raises concerns related to digital divides between large and small farms, as well as between farmers in industrialized and developing countries [4].



**Figure 1.** The conceptual scheme of “Agriculture 4.0”.

As the world’s largest developing country, China is characterized as a leading agricultural production country with a large proportion of smallholder farmers. Despite this, it has to feed more than 20% of the world’s population, with only 6% of fresh water and 7% of arable land in the world [5]. In recent decades, with the growing trend of urbanization and economic development, China has faced various agricultural challenges, including a dwindled supply of cropland, soil erosion, aquifer depletion, water pollution, and labor shortages. Digitally enabled agricultural technologies can make decision-making about input applications and crop management more autonomous and intelligent and thereby increase the productivity of land, reduce demand for labor, and minimize negative environmental impact. As a result, China has prioritized the digital transformation of agricultural technologies as part of its ongoing agricultural modernization efforts [6]. The federal government has implemented a series of regulatory policies to promote the development of digital agriculture (Table 1). In 2012, China published the 12th Five-Year Plan for National Agricultural and Rural Information Development. This report outlines the goals of constructing rural information infrastructure, which includes the implementation of advanced mobile communication networks, the internet, and satellite communication facilities. In late 2019, the Chinese government introduced the Digital Agriculture and Rural Development Plan (2019–2025), seeking to leverage digital innovations to support sustainable agriculture. In the recently released Digital Rural Development Action Plan for 2022–2025, the government emphasized upgrading digital infrastructure and developing smart farming in rural areas. These policies contribute to the steady growth of digital agriculture in the country [1]. However, the adoption of digital technologies in agricultural production in China is still slower than that observed in more affluent countries [7].

**Table 1.** Key policies promoting digital agriculture development in China.

Year	Policy Name	Core Content
2012	12th Five-Year Plan for National Agricultural and Rural Information Development	Promote the construction of rural information infrastructure
2013	Several Opinions on Accelerating the Development of Modern Agriculture	Develop agricultural information services, precise operations, rural remote digitalization and visualization and other technologies
2016	13th Five-Year Plan for National Agricultural and Rural Information Development	Advance the integration of information technology and agricultural modernization and promote the development of e-commerce in rural areas
2019	Digital Agriculture and Rural Development Plan (2019–2025)	Expedite the digital transformation of agricultural and rural production operations and management services
2022	Digital Rural Development Action Plan (2022–2025)	Upgrade digital infrastructure in rural areas and promote innovative development of smart farming

While these technologies offer technical improvements to agricultural production systems, their adoption is a complex process that is influenced by various factors [8]. Many of the so-called digital solutions are being developed in a manner that empowers the technology suppliers rather than assisting independent farmers in making well-informed decisions [9]. Furthermore, the potential benefits of digital technologies for farmers have not been fully demonstrated, and there has yet to be a direct policy in place to reward adoption [10,11]. Existing studies on digital transformation in the agricultural sector have primarily focused on the technical aspects of implementing technologies to improve agricultural productivity and practices. In recent years, an increasing number of studies have examined the adoption of these technologies by farmers and the key factors that influence their decision-making. Varying findings have been reported within the context of different technical and socioeconomic conditions. However, there are few systematic reviews that synthesize and integrate these findings. A comprehensive understanding of the factors that affect the adoption of these digital technologies has implications for both industrial practitioners and policymakers to incentivize the wide-scale application of these technologies.

This article aims to address this knowledge gap by conducting a systematic review of the determinants that affect the adoption of digital agricultural technologies in China, focusing on three objectives. The first is to characterize the factors of major influence in the adoption of digital technologies. The second objective is to briefly overview modeling approaches for examining the potential drivers of the adoption. The future direction of academic research is also provided. The third objective of this article is to discuss policy implications for promoting digital transformation in the agricultural production system.

## 2. Literature Review

The emergence of digital agricultural technologies (DATs) over the recent decades has been documented in many review studies. Typical types of digital technologies that have been available for adoption by farmers include the Internet of Things (IoT), big data and analytics, cloud computing, autonomous robotic systems, artificial intelligence, remote sensing, and drone technology. The beneficial impacts of these technologies on farm productivity, economic gains, efficiency enhancement, environmental protection, and sustainability have been addressed by technical-oriented literature [3,12–14]. For instance, small agricultural robots can improve weeding efficiency and work optimally with little interruption. By doing so, robots can reduce soil compaction and erosion [15]. Big data analytic techniques can be employed to assist farmers in the decision-making process, such as the application of irrigation water, fertilizer, and herbicides [16]. With the help of IoT-enabled systems combined with remote sensing, farmers can manage farms remotely, irrespective of place and time [17]. Artificial intelligence technology enables the collection

of georeferenced information on growing conditions in the field, which can make spatially precise application of inputs possible [18,19].

Despite the rapid growth and documented advantages of digital technologies, the adoption rate, particularly in developing countries, remains a challenge. It is increasingly understood that the adoption of digital agriculture is rooted in economic, political, and social relations, with a range of nontechnical issues being brought up [10,20]. As a result, these concerns have prompted researchers to explore farmers' intentions of technology adoption from a systematic perspective. A literature review by Rotz et al. [9] examined how political and economic factors affect digital transformation in the agrofood system. They acknowledged that political-economy-related challenges such as data ownership and security could hinder the extent to which digitalization can support the interests of farmers. Tey and Brindal [21] analyzed the underlying factors that influence the adoption of precision agricultural technologies by reviewing studies investigating the adoption in developed countries. Similarly, Lee et al. [22] conducted a systematic review of precision agriculture adoption worldwide. However, both studies primarily focused on early-generation tools and did not consider emerging digital technologies. Lowenberg-DeBoer and Erickson [23] reviewed existing studies on the adoption of various digital agricultural technologies globally. They discussed possible reasons that hamper the adoption of digital technologies by farmers, yet the factors identified remained incomplete because a systematic review of studies was absent. Khanna et al. [2] presented a perspective paper on the opportunities and challenges of adopting digital agricultural technologies in the United States. They summarized several economic and noneconomic factors expected to influence adoption decisions based on a nonsystematic review of the literature on the subject. However, their work only focused on the issue in the US, which is a relatively more experienced country in applying innovative technologies. Since the drivers of digital technology adoption differ greatly from country to country, it is not meaningful to draw conclusions from other countries' experiences [23]. The main components absent in existing literature are the integration and categorization of factors that influence technology adoption by farmers in China. This study will be valuable to digital transformation researchers and educators, agribusiness firms involved in selling digital tools, as well as policymakers concerned about sustainable agricultural production and farmers' welfare.

Within research, several methods have been applied to support the rigorous investigation of digital agricultural technology adoption. Existing studies analyzing farm-level adoption have typically used regression-based analysis (e.g., logit, probit, Poisson models) [12]. Due to the quantitative nature of these methods, they fail to capture qualitative factors, such as feedback from users in the form of opinions and suggestions. Some other studies adopt qualitative descriptive approaches accounting for less measurable factors such as material contingencies and cultural dimensions of knowledge [24]. Recently, some newly developed models placing greater emphasis on both quantitative and qualitative analysis have been applied to studying the adoption and diffusion of digital farming technologies, such as the Theoretical Framework of Acceptability [25]. In this study, we do not intend to review the existing methods used in the literature. Instead, we briefly overview modeling approaches for examining the determinants of farmers' adoption decisions in existing studies in China and discuss the limitations and possible improvements of these approaches.

The remainder of this paper is structured as follows. In Section 3, the literature search methodology is discussed. The results and discussion on identified factors and their implications are elaborated in Section 4. Section 5 concludes the paper.

### 3. Methodology

#### 3.1. Search Strategy

A systematic literature review (SLR) is a tool used to identify research articles related to a predetermined topic [26]. In this study, we carried out an SLR to identify the key factors that could affect farmers' adoption of DATs. The well-defined review protocol guarantees a robust systematic review process [27]. The protocol contains three components: the

formulation of research questions, the specification of the literature search strategy, and the establishment of inclusion and exclusion criteria. In this study, the ISI Web of Science database (accessed on 12 July 2023) was used as the primary tool for sample collection. The Web of Science database is an informative retrieval platform, which contains more than 9000 world-authoritative academic journals [28]. A web-based academic search engine, Google Scholar, was further applied since it was identified as a useful supplement to traditional academic citation databases [29]. The keywords used for this search are indicated in Table 2. Finally, to refine the search results, inclusion and exclusion criteria were applied for further validation of related publications. For instance, we limited the studies to those available in full text and published in English, excluding a portion of the gray literature, such as seminars summaries, books, reviews, and editorials. We did not apply any filters for the publication year to prevent missing any relevant literature. Note that in this article we mainly focused on on-farm technologies adopted by farmers. Off-farm technologies (in the agrifood value chains or more broadly food systems) adopted by agribusiness firms or supply chain management entities were not part of our review focus.

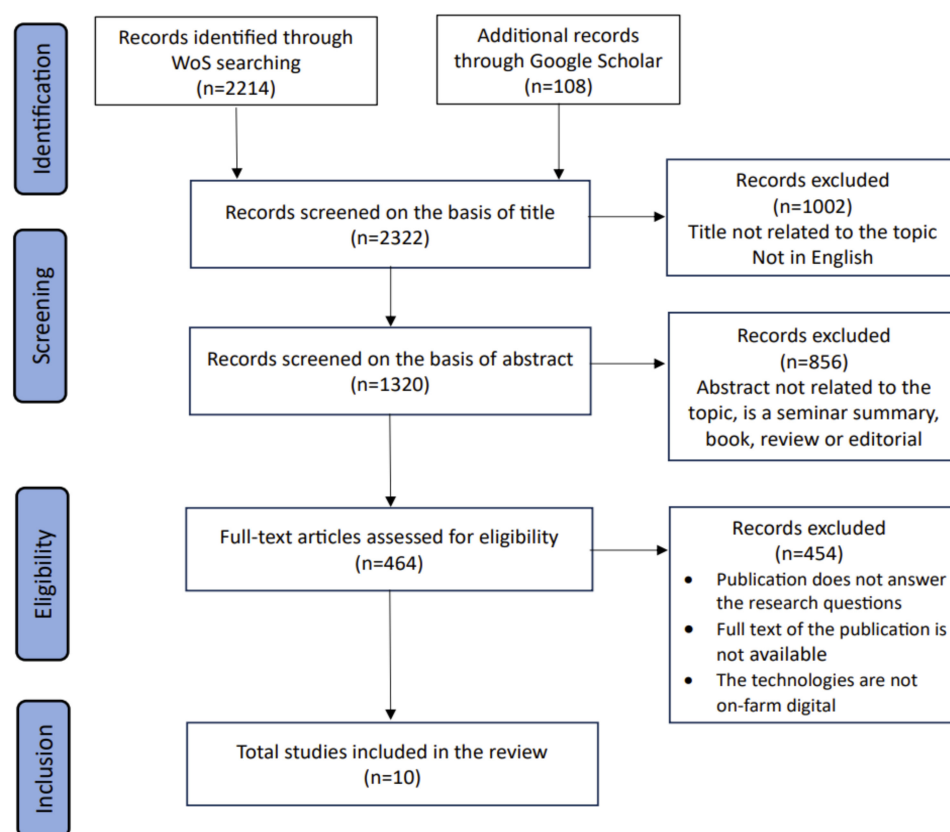
**Table 2.** Review protocol for systematic literature review.

<b>Review questions</b>	RQ1: What are the factors affecting farmers' decision to adopt digital agricultural technologies? RQ2: What are the analytical methods used for evaluating factors?
<b>Search strategy</b>	Sources: Web of Science and Google Scholar Search string: (("China") AND ("agriculture") AND ("digital technology" OR "Agriculture 4.0" or "Industry 4.0" OR "smart farming" OR "precision agriculture" OR "Internet of Things" OR "cloud computing" OR "artificial intelligence" OR "big data analytics" OR "robot" OR "remote sensing" OR "drone technology") AND ("farm*") AND ("adoption" OR "use" OR "application" OR "willingness" OR "intention"))
<b>Selection criteria</b>	Inclusion criteria: <ul style="list-style-type: none"> <li>• Peer-reviewed journal articles and grey literature.</li> <li>• Studies should provide answers to the research question.</li> </ul> Exclusion criteria: <ul style="list-style-type: none"> <li>• Summary of seminars and workshops, books, reviews, and editorials.</li> <li>• The publication is not in English.</li> <li>• The publication is not available in full text.</li> <li>• The technologies are not on-farm digital technologies.</li> </ul>

### 3.2. Study Selection

Figure 2 shows the search and screening stages for study selection. After initial filtering through the application of the search equation, a total of 2322 records were found. In the next stage, all papers were screened by reading their titles and abstracts. A total of 1320 records were selected after applying the limits for language (English only) and research topic. The number of publications was further reduced to 464 by excluding those that were not relevant to our interest and those that were in the form of seminar summaries, books, reviews, and editorials. In the final stage, a full-text screening was performed for these articles. Of the 464 papers, only 10 were found to be closely related to the subject of this review and were consequently selected for further analysis.





**Figure 2.** Diagrammatic flow of selected studies through the search and searching stages.

## 4. Results and Discussion

### 4.1. Overview of Reviewed Articles

Table 3 presents basic information about the 10 eligible articles. There is a predominance of ex-ante studies analyzing the acceptance of a new technology prior to the actual adoption. Only one article examined the ex-post determinants of the choice to adopt an existing technology. Their research encompassed the field from general digital agriculture to specific technologies (e.g., smart pesticide technology, IoT traceability technology, and unmanned aerial vehicles technology, etc.). The quantitative approaches employed in these articles were mainly regression modeling based on data gathered from surveys or interviews with farmers. The geographical regions surveyed in these studies were principally the main agricultural production regions across 11 provinces in China. The sample sizes in these articles ranged from 264 to 3890. The findings from these studies provide the empirical basis for our review analysis.

**Table 3.** Details of adoption analyses drawn from 10 reviewed studies.

Authors and Publication Year	Approach	Analytical Method	Studied Technology	Study Area	Farmer Type	Sample Size	No. of Variables	Model of Significance
Zhou et al. [30]	Ex-ante	Logit	General digital technology	National	General farmers	3890	14	Sig.
Yue et al. [31]	Ex-ante	Probit	Precision pesticide technology	Five provinces	Apple farmers	545	15	Sig.
Cai et al. [32]	Ex-ante	Probit	Digital pest and disease technology	Guangdong and Guangxi Province	Litchi farmers	901	18	Sig.
Sun et al. [33]	Ex-ante	Unified theory acceptance	IoT traceability technology	Shaanxi Province	Pig farmers	264	10	Sig.

Table 3. Cont.

Authors and Publication Year	Approach	Analytical Method	Studied Technology	Study Area	Farmer Type	Sample Size	No. of Variables	Model of Significance
Zheng et al. [34]	Ex-ante	Technology acceptance model	Unmanned aerial vehicles technology	Jilin Province	General farmers	897	10	Sig.
Liu et al. [35]	Ex-ante	Logit	Pesticide reduction technology	Hubei Province	Rice farmers	1193	17	Sig.
Wachenheim et al. [36]	Ex-ante	Probit	Unmanned aerial vehicles technology	Jilin Province	General farmers	854	19	Sig.
Lu et al. [37]	Ex-ante	Technology acceptance model	Agricultural information system	Jiangxi Province	General farmers	1504	11	Sig.
Li et al. [38]	Ex-ante	Structural equation model	Smart agriculture	Xinjiang Province	Cotton farmers	394	10	Sig.
Chen and Zhou [39]	Ex-post	Gradual regression	Green smart agriculture technology	Jiangsu Province	Rice farmers	782	8	Sig.

#### 4.2. Identification and Categorization of Factors

Derived from the 10 selected studies, we have identified a total of 19 significant factors that contribute to the decision to adopt DATs. As indicated in Table 4, these factors can be distributed into five major categories, which are socioeconomic, agroecological, technological, institutional, psychological, and behavioral. The role of each of these categories is discussed in the subsequent subsections.

Table 4. Significant factors influencing the adoption DATs.

Categories of Factors	Significant Variables	Effects	References
Socioeconomic factors	Age	Positive	Zhou et al. [30]; Cai et al. [32]
	Gender-female	Negative	Zhou et al. [30]; Zheng et al. [34]; Wachenheim et al. [36]
	Education	Positive	Zhou et al. [30]; Cai et al. [32]; Liu et al. [35]
	Health	Positive	Zhou et al. [30]; Cai et al. [32]
	Total income	Inconclusive	Cai et al. [32]; Liu et al. [35]; Wachenheim et al. [36]
	Agricultural income	Positive	Chen and Zhou [39]; Zheng et al. [34]; Wachenheim et al. [36]
	Farming experience	Positive	Zhou et al. [30]; Yue et al. [31]
	Member of cooperatives	Positive	Yue et al. [31]; Cai et al. [32]
Agroecological factors	Farm size	Positive	Yue et al. [31]; Liu et al. [35]; Wachenheim et al. [36]
Technological factors	Access to digital information	Positive	Yue et al. [31]; Cai et al. [32]; Li et al. [38]
	Cost of technology	Negative	Liu et al. [35]
Institutional factors	Government subsidy	Positive	Zhou et al. [30]; Liu et al. [35]; Li et al. [38]; Lu et al. [37]
	Availability of financial services	Positive	Yue et al. [31]; Wachenheim et al. [36]
	Environmental regulation	Positive	Yue et al. [31]
	Extension services	Positive	Yue et al. [31]; Liu et al. [35]
	Contract farming	Positive	Chen and Zhou [39]
Psychological and behavioral factors	Perceived profitability of using technology	Positive	Yue et al. [31]; Zheng et al. [34]; Li et al. [38]; Lu et al. [37]
	Perceived ease of using technology	Positive	Sun et al. [33]; Zheng et al. [34]
	Risk perception	Negative	Sun et al. [33]; Liu et al. [35]; Li et al. [38]

#### 4.2.1. Socioeconomic Factors

Socioeconomic factors refer to the personal background of the primary decision-maker of the farm. Information-intensive technologies usually require a high level of human capital. As such, the farmers' capacities and knowledge clearly influence their adoption decision to use DATs. Various socioeconomic factors have been incorporated into analytical models as explanatory variables [30,32,34–36]. Significant socioeconomic factors identified in the reviewed papers include age, gender, education level, health status, income (including total income and percentage of agricultural income), farming experience, and cooperative membership. Younger farmers have been shown to be more willing to adopt innovative technologies than their older counterparts. This has been explained as a consequence of younger farmers having longer planning horizons and being more technologically-oriented [40]. The effect of gender on DAT adoption reflects a disparity in preferences for innovative agricultural technologies. Female farmers, often serving as agricultural assistants and lacking resources, may be less likely to accept new technologies [37]. Formal education attainment is found to correlate positively with the adoption of DATs, as digital technologies require knowledge-based skills and interpretation [30,32,35]. A couple of studies have found a significant impact of health status on the adoption of on-farm digital technologies [30,32]. Farming experience likewise has a positive impact on farmers' adoption. This could be because healthier and more experienced farmers may feel less reliant on the additional support provided by others during the implementation process and are, therefore, more open to embracing advanced technologies. Other research has shown that farmers involved in cooperatives are more likely to express a willingness to adopt these technologies [30,31]. In most cases, cooperatives are associated with collective action and social capital, which can consequently provide vital information to facilitate farmers' adoption. In contrast to the aforementioned socioeconomic factors, there is no consensus in the literature on the impact of household income. Total household income could have either a positive [32,35], negative [36], or no significant influence [30,37] on DAT adoption. In view of this mixed picture, the total household income does not lend itself to an easy indicator for adoptive decisions. Instead, other wealth-related factors, such as agricultural income ratio [34] or agricultural income [39], are more effective in predicting farmers' decision to adopt.

#### 4.2.2. Agroecological Factors

Agroecological factors embody on-farm natural endowments (e.g., land and vegetation) and operational factors (e.g., cultivated acreage). Farm size, measured as the total land available to farmers for agricultural production, is a significant factor. Larger farms tend to have a greater capacity to make investments and absorb costs and risks. Consequently, in many cases, farmers with a larger cultivated land area are more inclined to adopt digital technologies [31,35,36]. In the studies reviewed here, factors related to natural endowments, such as soil quality, crop yield, and past weather disturbances, have not been thoroughly examined.

#### 4.2.3. Technological Factors

Technology attributes, such as complexity in handling equipment and data, costs of technology implementation, and trialability, are important determinants of DAT adoption. Low-cost equipment could motivate farmers to adopt this new technology, especially among smallholder farmers [35]. Yue et al. [31] found that access to digital information plays a positive role in precision pesticide technology adoption through services and equipment acquisition. Farmers using the Internet to acquire timely agricultural technology information are more likely to adopt novel technologies. The adoption rate might be further accelerated through improved training and the availability of digital infrastructure [41].

#### 4.2.4. Institutional Factors

The roles that institutions such as private entities, collectives, and government agencies play are essential for the uptake of agricultural innovation. Several studies have shown



that government subsidies can significantly increase farmers' willingness to adopt digital technologies [30,35,37]. Availability of financial and extension services are also influential factors for technology adoption, especially among small-scale farmers. Chen and Zhou's research [39] indicates that contract farming can stimulate farmers' use of smart agriculture technologies. These findings imply that reliable support from the government or collectives is effective for farmers to take up new farming practices.

#### 4.2.5. Psychological and Behavioral Factors

Adoption of new technologies is never a purely technical problem. It relies highly the behavior changes of stakeholders, which are influenced by their beliefs and attitudes. A risk-neutral farmer is likely to adopt a technology that results in net increases in operating profits [42]. Many studies show that the perception of profitability with new technologies significantly drives the intention of adoption [31,34,37,38]. In addition to the profitability of alternative technologies, the riskiness of those profits can also impact the decisions of risk-averse farmers [33,35,38]. Since novel digital technologies often come with more economic uncertainty and technical difficulty than traditional ones, research has confirmed that the perceived ease of utilizing these technologies increases farmers' adoption of digital technologies [33,34].

Extrapolated from the discussion in the earlier section, the adoption of DATs is a result of multidimensional considerations. It is positively associated with (1) socioeconomic factors (farmers who are younger, male, healthy, better educated, cooperative members, and have a higher agricultural income and more farming experience), (2) agroecological factors (farmers who own larger cultivated areas), (3) technological factors (the lower cost of technology and access to the digital information), (4) institutional factors (farmers who receive government subsidy or financial services, engage in contract farming, or face pressure for environmental sustainability), and (5) psychological and behavioral factors (farmers who perceive that DATs are profitable and easy to use).

It is worth noting that farmer and farm characteristics such as education, income levels, and farm size are considered relatively "fixed" determinants and are not often included as potentially important variables in studies conducted in developed countries [40]. Socioeconomic factors are relatively stable within developed countries, which could explain why these factors are not always significant in studies carried out in such countries. However, this review shows that these characteristics are important determinants of farmers' adoptive decision in China. Agriculture in China is often characterized by small-scale farming and significant heterogeneity among different provinces in terms of cultivated area [43]. In recent years, with the continual development of the economy and the introduction of rural revitalization policies, there has been a notable expansion in the farming scale, accompanied by improved health and income standards for rural laborers. In the face of the rapid change in rural operations and the labor force structure, it is still crucial to consider socioeconomic factors in the design of empirical studies.

Among all five groups of factors, agroecological factors are the least explored in existing studies. Farm size is the only variable considered in this group. Studies focusing on other countries have found that factors such as soil quality, availability of irrigation water, previous weather shocks, and crop yields are influential determinants in the adoption of DATs. These studies reveal that farmers value agricultural innovations that are adaptable to natural conditions and environmental changes. Overlooking such features in research may lead to a skewed understanding of adoption decisions.

The decision of most farmers to adopt new technology is typically driven by its potential to increase profitability or generate direct revenue. As expected, the cost of technology negatively affects adoption. However, some institutional factors such as government subsidies, contract farming, and agricultural extension services can incentivize farmers to adopt new technology despite the associated costs. There is a growing literature going beyond profit maximization as incentives for adoption to examining the role of psychological and behavioral factors in explaining the technology adoption and diffusion process. Findings

suggest that the perceived usefulness, ease, and risk of adopting new technologies play a significant role in decision-making, highlighting the importance of cognitively linked factors. Institutional and behavioral factors are relatively modifiable, through which intervention has an opportunity to boost the likelihood of DAT adoption. For instance, public education on environmental damage and changing climate can raise awareness of sustainability. However, this social pressure may not be effective if there is insufficient stimulant. Lehman et al. [44] emphasized that a farmer still might adopt a new agricultural technology even though they may not perceive profitability. This is made possible through financial support and technical assistance. Institutional factors could indirectly reshape farmers' perceptions and increase actual rates of adoption.

#### 4.3. The Role of Methods

A large body of studies has examined the adoption of early-generation precision agricultural technologies. These studies typically conduct the ex-post analysis to explain the incentives and challenges involved in adopting an existing technology. However, our review study reveals that the majority of empirical work analyzing the adoption of digital technologies in China utilizes an ex-ante approach. This is largely due to the fact that many digital technologies have not been implemented on a commercial scale, and there is insufficient data available. Ex-ante analysis can be beneficial in evaluating the attributes of the technology and potential obstacles to adoption.

Unlike traditional technologies, digital agricultural technologies typically have a multifaceted and complex nature. They encompass different components, data acquisition, data analysis, and technology application choices [45]. Adoption of digital technologies is, therefore, more complicated than a simple binary choice decision. Instead, farmers often start with on-farm trials and adopt components sequentially. Stated preference methods, specifically contingent valuation methods and choice experiments, are commonly used to determine a farmer's ex-ante decision (e.g., willingness to adopt or willingness to pay for new agricultural technologies). However, in a contingent valuation survey, as employed in most of the surveyed studies, respondents are typically asked about a technology possessing specific attributes. As a result, this method does not allow for the evaluation of multiple attributes in the adoption decision. A choice experiment is an alternative approach which enables respondents to choose from multiple technology attributes and related outcomes. Furthermore, it can be designed to examine the influence of neighborhood effects on the adoption decision. Learning from extension agents, neighboring farmers and virtual social networks play a strong role in the initial acceptance of new agricultural technology [46]. However, the surveyed studies have rarely explored the influence of social networks and spillovers.

The implementation of new technologies is a learning endeavor requiring trial evaluation, gradual adoption, review, and modification practices. Optimal frameworks would allow researchers to view adoption as a dynamic process rather than a fixed intention. Researchers would benefit from introducing diverse methodologies into their empirical studies, such as randomized control trials, agent-based models and experiments, and games in surveys. The application of advances in behavior economics can be effective in examining the impact of cognitive factors, social pressure, trust in information providers, and other elements on adoption decisions. Despite recognizing the heterogeneity of the adoption and specificity in terms of technology and local conditions, current research has not yet provided a direct measurement to fill this gap. Therefore, the combination of multi- and transdisciplinary models from economics, digital technology, agronomy, and social psychology are increasingly recommended to explain the adoption decision [47]. Existing empirical studies in China are significantly fewer than those performed in more experienced countries, and they often overlook the complex nature of digital technologies and potential adopters. Hence, research should persist in identifying potential trigger factors and seek to provide insights on the adoption of these emerging technologies, which might differ considerably from traditional technologies.

#### 4.4. Policy Implications

Even though the Chinese government has supported the development of digital technologies in the agricultural sector through various policies, a significant share of farmers is yet to adopt any of these technologies due to varying concerns. This review reveals key motivating factors that, if addressed, could assist agencies and the government in overcoming adoption constraints. By formulating more targeted strategies according to the farmers' characteristics and the features of the technology, public efforts could help transform the numerous trial examples of digital agriculture into viable industries and spread benefits to a larger group of farmers. Potential interventions could involve offering knowledge training and extension services, establishing farm cooperatives, and implementing environmental regulations.

Adoption may not occur if DATs are not demonstrated to be more cost-effective than traditional methods, given that the farming business is profit-orientated. Financial initiatives such as capital subsidies, cuts in interest rates, and enhanced financial services can play an important role in motivating the adoption of digital technologies, especially among small-scale farmers. These incentives need to be performance-oriented and farm-specific instead of being uniformly applied across all farmers and regions.

Additional challenges for the wide adoption of DATs include insufficient information and communication technology (ICT) literacy, inadequate supporting services and infrastructure, and an unreliable supply of electricity and Internet. Public entities can participate in supplying digital services and infrastructure, establishing open standards and protocols, and creating platforms for communication and information sharing. By providing access to agroeconomic data, connectivity, and environmental outcomes of production decisions, public action can harness the opportunities created by digital technologies and facilitate the digital transformation in agricultural production.

Digital technologies are characterized by aggregating high-resolution data from multiple sources, including privately owned data, remote sensor data, and public data. Concerns about data ownership, privacy, and confidentiality can pose additional barriers to adoption, as farmers are likely to perceive less control over their farm operations. Accordingly, appropriate policy should shape regulatory conditions concerning how and by whom the collected data is maintained and controlled. By offering clear guidelines and security on data-related issues, public initiatives can reduce the riskiness perceived by technology adopters.

#### 5. Conclusions

Emerging DATs are rapidly evolving, offering unprecedented opportunities for the global agricultural sector. These technologies have the potential to enhance efficiency, economic gains, and environmental friendliness in agricultural production and contribute to higher productivity. This is especially appealing to developing nations in search of solutions to food security and environmental sustainability a changing climate. Empirical studies on DAT adoption in China have rarely been discussed in the systematic review of global experience, primarily due to the overwhelming literature focused on developed countries. This paper offers the first systematic review of literature on factors influencing farmers' adoption of DATs in China. We conclude that farmers' adoption decision is a result of multidimensional considerations. Significant factors that can help predict the adoption decision can be categorized into five groups: socioeconomic factors, agroecological factors, technological factors, institutional factors, and psychological and behavioral factors.

The stated preference method is predominantly utilized to determine a farmer's hypothetical willingness to adopt digital technologies in existing studies. However, this method has limitations in eliciting information about adopting complex digital technologies with multidimensional components. More comprehensive modeling tools integrating concepts from both social science and natural science are recommended to explain the complex and heterogeneous nature of technology adoption by farmers. These can be advanced models that take account of both quantitative and qualitative dimensions of

adoption. The stated preference method can also be combined with agent-based models to simulate adoption dynamics and systemic diffusion mechanisms.

This study further analyzes and synthesizes past knowledge to identify bases for future research and policy development. By addressing this, new insights on the pathway to improving adoption rates can be provided to practitioners, researchers, and policymakers. Accelerating the adoption and diffusion of digital technologies in rural areas requires multicooperation among individuals, extension agents, governments, and technology providers. Policy instruments can play an important role in supporting farmers' accessibility to services and information, improving their knowledge and skills, and reducing their perception of risks.

As digital agriculture is increasingly moving beyond the hype and prototype stages, our review is timely in presenting opportunities for transforming the concept into reality. The capabilities of digital technologies are developing rapidly, and their costs are anticipated to decline in the future. Although our paper offers valuable insights applicable to these emerging technologies, more comprehensive research is needed to bridge the gap between technical innovations and their applications. In doing so, it can help to guide the development of digital agriculture in ways not only for private gains but also for societal benefits.

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