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Challenges to artificial intelligence-enabled digital technology adoption in farms: a multi-method approach

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Abstract

Artificial intelligence (AI)-enabled digital technologies have the potential to transform agriculture by supporting decision-making and automating operations. However, their limited adoptions and scholars' atheoretical explorations constrain our understanding. Drawing on the technology-organization-environment (TOE) framework, we investigate the challenges hindering the AI-enabled technology's adoption in farms using a multi-method approach, including semi-structured interviews, thematic analysis, total interpretive structural modeling, and fuzzy cross-impact matrix multiplication applied to classification analysis. Our finding shows novelty in several aspects. First, we identify 13 challenges, some of which are underexplored, such as the absence of effective intermediaries in promoting agricultural technology. Second, we developed a hierarchical and clustering framework to reveal their interrelationships, classifications, and identify the key challenges. Third, we reorganize the TOE framework into a P-TOE model, where "P" represents people's experience, knowledge, and skills. Finally, we offer practical recommendations, including the creation of non-profit technology extension hubs and hands-on training programs to promote inclusive technology adoption.

Keywords: artificial intelligence; digital technologies; farming; decision-making; total interpretive structural modeling; MICMAC analysis

1. Introduction

Artificial intelligence (AI) can be broadly defined as the simulation of human intelligence by machines or systems (Akpan et al., 2025). It encompasses a wide range of capabilities aimed at replicating human behaviors, including perception, reasoning, learning, and problem-solving (Rashid and

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Kausik, 2024). Due to its potential to enhance efficiency, improve accuracy, and support more informed decision-making, AI is increasingly being adopted across diverse sectors, including agriculture (Camacho et al., 2026; Dipierro et al., 2026). For example, AI can be used to analyze disaster-related data to support effective disaster management (Sun et al., 2020), enhance healthcare delivery through applications such as diagnostic imaging, autonomous medical devices, and patient monitoring (Bohr and Memarzadeh, 2020), and optimize transportation systems by reducing congestion and improving travel reliability (Iyer, 2021). In the agricultural sector, AI-enabled technologies have shown promise in areas such as crop selection, yield prediction, water resource management, and soil compatibility analysis (Akkem et al., 2023; Bang et al., 2023). Despite these potential benefits, the adoption of AI in agriculture remains relatively limited, primarily due to a range of challenges.

Scholars have examined the challenges hindering the adoption of AI-enabled digital technologies in agriculture from various perspectives. For example, Mhlanga and Ndhlovu (2023) conducted a literature review to assess the level of digitalization in African farming and identified key barriers to its advancement. Similarly, Dibbern et al. (2024) reviewed the primary drivers and obstacles influencing the adoption of digital agricultural technologies. Among the most frequently cited barriers are a lack of trust, aging farming populations, limited technological literacy, Internet connectivity issues, and concerns over data security and privacy. Limpamont et al. (2024) proposed a framework categorizing these challenges into two broad types: farmer-specific challenges and ecosystem-related challenges. The former encompasses the individual-level barriers faced by farmers, while the latter includes external systemic factors that affect technological uptake. In a related study, Marshall et al. (2022) conducted an empirical case study on digital agri-tech adoption in Australian farms, revealing that technological, discursive, and social factors all play a critical role in shaping adoption decisions. Most of the existing literature focuses on identifying, categorizing, and addressing the challenges associated with the adoption of AI-enabled digital agricultural technologies. However, relatively little research has offered a hierarchical and a clustering framework to systematically understand and structure these challenges (Silveira et al., 2023a). The interconnected nature of these challenges creates a complex landscape, making it difficult for farmers to effectively navigate and overcome them (Costa et al., 2023).

This study conducts a comprehensive analysis of the challenges associated with the adoption of AI-enabled digital technologies on farms by identifying various challenges, mapping their interrelationships, and uncovering the most influential challenges. To guide this investigation, three research questions are formulated: (1) What are the challenges to the adoption of AI-enabled digital technologies on farms? (2) How are these challenges interrelated? (3) What are the key challenges that possess the highest capacity to trigger other challenges in the system? By addressing these questions, this study makes the following contributions. First, it enriches the digital adoption literature by systematically identifying a wide range of challenges. Notable challenges are the absence of effective intermediaries in promoting agricultural technology, and access to government subsidies often depends on *guanxi*. *Guanxi* is the system of social networks and relationships (Davison et al., 2018), which often plays a critical role in farmers' access to government subsidies in China. Second, this study constructs a hierarchical framework that reveals the interrelationships among the identified challenges. Third, this study distinguishes the challenge's capabilities to induce other challenges, thereby enabling the clustering of them. Finally, this study reorganizes the technology-organization-environment (TOE) framework by highlighting the P-TOE

model, in which “P” represents individual-level (personal) factors that affect technology adoption decisions.

The remainder of this study is structured as follows. In Section 2, the TOE framework, the diverse applications of AI-enabled digital technologies in agriculture, and relevant adoption challenges are reviewed to identify existing research gaps. In Section 3, we justified the research methodology adopted, followed by Section 4, which outlines the empirical data collection process conducted in China. In Section 5, we described each data analysis method adopted and presented the key findings. In Section 6, we compared our findings with those of previous research to highlight our unique contributions. Finally, we draw our conclusions in Section 7.

2. Literature review

In this section, we begin by reviewing the TOE framework to establish the theoretical foundation for the study. We then examine the range of digital technologies currently implemented on farms, along with the key challenges that hinder their adoption by farmers. Finally, we identify critical research gaps, highlighting promising directions for future investigations.

2.1. TOE framework

The TOE framework is a theoretical framework that was developed in the field of information systems to explain how the adoption and use of new technologies are influenced by technological, organizational, and environmental factors (Tornatzky and Fleischer, 1990). As an organizational-level theory, it posits that these three contextual dimensions collectively influence a firm’s technology adoption decisions. Factors from the environmental context, such as government regulations, technological support infrastructure, industry characteristics, and market structure, can influence technology adoption at the organizational level. Similarly, factors from the organizational context, including communication processes and both formal and informal linking structures, and from the technological context, such as the availability and characteristics of the technology itself, all play a role in shaping adoption decisions (Rogers, 1995).

Several scholars have employed the TOE framework to investigate the adoptions of various digital technologies. For example, Chittipaka et al. (2023) used the TOE framework to examine the factors influencing the adoption of blockchain technology in supply chain operations. Awa and Ojiabo (2016) applied the TOE framework to explore the determinants of enterprise resource planning (ERP) adoption among small- and medium-sized enterprises (SMEs). Similarly, Raj and Jeyaraj (2023) utilized the TOE framework to analyze the factors affecting the adoption of Industry 4.0 (I4.0) technologies. Without focusing on specified digital technologies, Zhang and Wang (2024) applied the TOE framework to the context of pre-cooked meal companies’ overseas supply chains. Their analysis revealed that technical factors (e.g., intelligent information technology and automation), organizational factors (e.g., talent and social adaptability), and environmental factors (e.g., market adaptability) all exert positive influences on the sustainability performance of these companies. Building on the same theoretical framework, Luo et al. (2025) demonstrated

that technical factors (e.g., digital infrastructure and agricultural technological innovation), organizational factors (e.g., supportive policies), and environmental factors (e.g., modernization of rural culture) play a significant role in driving the digital transformation of the agricultural industry. Scholars have also adopted other theoretical frameworks to examine the adoption of digital technologies. For example, Cao et al. (2025) utilized technology acceptance model (TAM) and TOE framework for farmer cooperatives and found that perceived ease of use and perceived usefulness significantly increased adoption intentions. They further observed that government support and competitive advantage enhanced cooperatives' perceptions of both ease of use and usefulness. Building on similar theoretical underpinnings, Wang et al. (2019) reported that environmental factors positively influenced agricultural information technology adoption intentions, whereas technological factors did not exert a significant effect. Importantly, their findings underscored the mediating role of leaders' attitudes in shaping the relationship between environmental and technological conditions and adoption intentions. In contrast to studies drawn on the TAM and TOE frameworks, Smidt and Jokonya (2022) adopted the choice framework to provide a holistic analysis of the social, political, and economic factors shaping small-scale farmers' adoption of digital technologies. Giua et al. (2022) drew on the unified theory of acceptance and use of technology (UTAUT) to examine the determinants of smart farming technology adoption. Finally, Dissanayake et al. (2022) conducted a comprehensive review of technology adoption studies in the agricultural sector and identified 20 frequently employed theories and models, including TAM, UTAUT, diffusion of innovation, TOE, social cognitive theory, and theory of interpersonal behavior.

In this study, we utilized the TOE framework to investigate the challenges affecting the adoption of AI-enabled digital technologies on farms for several reasons. First, existing studies have employed a range of theories, models, and frameworks to examine factors influencing the adoption of digital technologies in the agricultural sector. However, these theories, models, and frameworks have limitations that make them less suitable for the present study. For example, the TAM is widely used to explain how individuals accept and use new technologies (Davis, 1989), but it primarily focuses on the individual level of analysis and does not capture organizational or environmental influences. The UTAUT addresses broader behavioral influences, with key constructs including performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). However, it still primarily emphasizes the individual level of analysis and the role of social context. Similarly, the diffusion of innovation theory can be viewed as a complement to TAM and UTAUT, but it predominantly focuses on the individual level of analysis, offering limited insight into environmental or institutional factors (Rogers, 1995). Key constructs include relative advantage, compatibility, complexity, trialability, and observability. The TOE framework, by encompassing technological, organizational, and environmental dimensions, provides a more comprehensive lens and is therefore particularly suitable for this study. Second, AI-enabled digital technologies are typically expensive, making them difficult for individual farmers to adopt but more feasible for farming cooperatives/enterprises. Moreover, cooperatives/enterprises tend to place greater emphasis on the technological capabilities of AI-enabled digital technologies and are more susceptible to external environmental influences. This is supported by our fieldworks in China. Third, the TOE framework is a well-developed and extensively validated theory, providing a solid foundation and empirical support for developing our study.

Based on these considerations, the TOE framework was deemed appropriate for guiding our investigation.

2.2. The application of AI-enabled digital technologies on farms

The application of AI-enabled digital technologies in agriculture can be traced back to expert systems, which are specialized software applications capable of performing reasoning and analytical functions within narrowly defined domains at levels approaching human expertise (Coulson et al., 1987). Such systems promised potential benefits for farm management and therefore developed to provide decision support in areas such as irrigation, nutrient and fertilizer management, weed control, crop cultivation, and pest management (McKinion and Lemmon, 1985). However, Doluschitz and Schmisser (1988) cautioned that although expert systems could be applied to various domains of farm management, the choice of application areas needed to be carefully made, given the time-consuming and costly nature of system developments. Similarly, Nitsch (1990) emphasized that the design of such systems should enable farmers to engage with computer-based information in an active, critical, and effective manner.

Due to vastly increased and affordable computational power, various AI-enabled digital technologies are increasingly being applied on farms to enhance monitoring, guide agricultural actions, and enable accurate predictions, thereby improving overall farm efficiency and productivity. For example, the integration of sensors, satellite imagery, drones, and AI algorithms can be used to monitor crop health. More specifically, AI programs can analyze drone footage to detect potential threats such as animals, birds, or unauthorized individuals that may damage crops (Javaid et al., 2023). AI is also used to detect plant diseases by leveraging high-resolution cameras and Internet of Things (IoT) devices and offering pest control recommendations based on expert knowledge or information retrieved from online sources (Partel et al., 2021). A practical example is provided by Papadimitriou (2012), who highlights how AI algorithms can effectively detect small insect intrusions. Once detected, alerts are instantly sent to farmers' smartphones, enabling timely intervention. Furthermore, the application of AI in agriculture has significantly improved decision-making processes. For example, sensors are widely used to collect data on temperature, weather conditions, water usage, soil quality, and other farm-related parameters. These data are then processed by AI systems on digital platforms, providing farmers with actionable insights to make informed decisions (Hemming et al., 2019). AI also plays an effective role in reducing resource consumption by analyzing historical data on resource allocation and usage and by recommending optimized alternatives for more efficient management. For example, Addas et al. (2024) developed a robotic crop farming prototype supported by deep reinforcement learning to optimize resource management. Their simulation results demonstrated that this technology could increase crop yield by 26%, while reducing water use by 41% and agrichemical use by 33%. In Europe, the application of AI-driven technologies, such as optimized spray timing, variable rate application maps, and product recommendations, has resulted in a 30% decrease in fungicide usage on field-trial cereal crops and a 72% reduction in tank leftovers, thereby mitigating environmental pollution (Shankar et al., 2020). In addition to resource optimization, scholars have identified several other benefits of applying AI-enabled digital technologies in agriculture. These include crop and soil monitoring, detection of soil defects, support for food supply chain management, enhancement of agricultural yield and

productivity, assistance in crop cultivation and harvesting, tackling labor shortage, and facilitation of precision agriculture practices (Jha et al., 2019). A notable example is the integration of AI, IoT, and autonomous tractors, which offers an effective solution to labor shortages by automating various farming tasks. Despite significant benefits promised by AI-enabled digital technologies for agriculture, their adoption has lagged behind other industries due to multiple challenges (Abbasi et al., 2022). For example, while the U.S. agriculture and manufacturing sectors are of similar size, the market value of AI is estimated to be nearly five times greater than in agriculture (Federal Reserve Bank of St. Louis, 2024; Thomasson et al., 2025). A recent report commissioned by the European Commission on how AI can support more sustainable and resilient agricultural practices in Europe (Rauch et al., 2025) shows that although AI technologies for agriculture are advancing rapidly, their adoption remains uneven. We contend that a range of unique challenges faced by farmers and the agricultural sector more broadly continue to impede the adoption of AI in farming.

2.3. Challenges impeding the adoption of AI-enabled digital technologies in the agri-food sector

While farmers are gradually adopting new technologies, the overall pace of adoption remains relatively slow (Trendov et al., 2019). For example, the OECD report on agricultural digitalization (McFadden et al., 2022) indicates that across all farm types and technology categories, digital technology adoption rates in England increased by only 6%–9% from 2012 to 2019, with substantial geographical disparities observed. The report further concludes that although large farms have the strongest incentives to adopt digital technologies, adoption remains uneven and far from universal across the sector. The adoption of AI-enabled digital technologies is progressing even more slowly. In indoor farming, the market share for AI adoption slightly declined from 15.2% in 2019 to 15% in 2024. Meanwhile, livestock farming saw a marginal 1% increase, and field farming experienced an even smaller rise of just 0.4% over the same five-year period (Scoutlabs, 2025). A range of challenges has contributed to the sluggish adoption of AI-enabled digital technologies in agriculture. For example, Aijaz et al. (2025) identified four categories of barriers hindering the adoption of AI-integrated agricultural systems: technological, social, regulatory, and economic impediments. Similarly, Thomasson et al. (2025) outlined seven major challenges in developing AI for agriculture, including limited applicability of AI models, lack of connectivity, data incompatibility, data privacy concerns, resistance to change, high adoption costs, and shortages of an AI-skilled workforce. Tzachor (2021) further emphasized 18 barriers to adoption, with the most critical being farmers' lack of trust in the technology and the language and literacy barriers associated with the digital divide. Echoing this concern, Gardezi et al. (2024) also argued that low levels of trust among farmers constitute a key obstacle to the adoption of AI-enabled digital technologies on farms. In a systematic review of 39 peer-reviewed studies published between 2010 and 2024, Erike et al. (2025) synthesized eight categories of challenges specific to AI applications in poultry farming: data quality and imbalance, model generalization and scalability, computational and resource limitations, occlusion and lighting variability, model interpretability, dependence on hardware and infrastructure, application adoptability, and hyper-parameter optimization.

To establish a solid theoretical foundation and inform subsequent empirical research, we conducted a systematic literature review on the topic. Previous reviews on agriculture and AI were examined to identify relevant keywords for guiding the literature search in this study, including Jha et al.'s (2019) review on automation in agriculture using AI, Bao and Xie's (2022) review on AI in animal farming, Akkem et al.'s (2023) review on smart farming with AI, and Erike et al.'s (2025) review on AI applications and challenges in precision agriculture. The keywords derived from these studies were combined into the following search string: (“artificial intelligence” OR “deep learning” OR “machine learning”) AND (“agriculture” OR “farming” OR “agri-food”) AND (“challenges” OR “barriers” OR “inhibitors” OR “prohibitors” OR “factors” OR “determinants”). Searches were conducted in Web of Science, ScienceDirect, and Taylor & Francis Online, as these databases include the world's major journals, conference proceedings, and book chapters, with strong coverage of business and management scholarship, and are widely used in literature reviews. The initial search yielded 1540 publications. These records were imported into EndNote 2025, and duplicates were removed using the “find duplicates” command, reducing the dataset to 847 publications. To further refine the selection, we applied several inclusion criteria. Specifically, only peer-reviewed journal articles written in English and accessible in full text were retained, while conference proceedings, book chapters, editorial materials, and inaccessible papers were excluded. This step further reduced the number of publications to 421. For example, some book chapters such as Nitsch (1990), which focuses on farmers and computers, were not included for further analysis. We then screened each paper's title, abstract, keywords, introduction, and conclusion to ensure that the selected publications had a clear focus on the challenges of applying AI in agriculture. To ensure the relevance and quality of the selected studies, two Ph.D. students with research interests in agriculture and food systems independently reviewed each publication. In cases of disagreement regarding inclusion, a professor of operations management with over 10 years of experience collaborating with the agri-food industry was consulted to make the final decision. This step further reduced the dataset to 58 publications. Studies such as McKinion and Lemmon (1985) and Doluschitz and Schmisser (1988), which focus on expert systems for agriculture, were not included for further analysis. The remaining articles were read in full to assess their relevance, resulting in the inclusion of 30 journal papers for the final analysis. For example, some papers such as Georgopoulos et al. (2023) and Sood et al. (2024) examine factors or determinants influencing the adoption of AI in agriculture and explicitly identify related challenges; therefore, these studies were included for further analysis. Other studies, such as Ganeshkumar et al. (2023), Silveira et al. (2023a), and Kaushik et al. (2024), focus on Agriculture 4.0, I4.0, and technology adoption in the agricultural sector but explicitly state that AI is one of the technologies considered; hence, these studies were also included for further analysis.

Table 1 presents detailed information on the 30 selected studies. The 30 selected studies were not chosen merely for thematic overlap but for their analytical alignment with the research questions and the core dimensions of challenges associated with the adoption of AI-enabled digital technologies in agriculture. While studies such as Mohr and Kuhl (2021), Holzinger et al. (2022), Marvin et al. (2022), and Erike et al. (2025) provide in-depth insights into specific AI-enabled digital technology adoption challenges, we intentionally integrated broader I4.0 and smart farming literature (e.g., Rodzi et al., 2024; Srinivasan and Yadav, 2024; Narayanamurthy et al., 2025). This was a deliberate conceptual choice, as these studies offer a socio-technical perspective into systemic challenges such as cultural norms, regulatory frameworks, and institutional constraints that

Table 1
Summary of studies on adoption challenges of smart agricultural technologies

Author(s) (year)	Topic focused	Theory adopted	Research methodology adopted	Modeling techniques used	Country focused
Mohr and Kuhl (2021)	Acceptance of artificial intelligence (AI) in Germany agriculture	Technology acceptance model (TAM) and theory of planned behavior	Surveys and modeling	Structural equation modeling	Germany
Holzinger et al. (2022)	Digital transformation in smart farm with human-centered AI	Not specified	Theoretical and conceptual	N/A	Not specified
Kasemi et al. (2022)	Barrier identification to fill the gap between technology and agriculture	Not specified	Surveys	N/A	Serbia
Marvin et al. (2022)	Digitalization and AI for sustainable food systems	Not specified	Literature reviews	N/A	N/A
Ganeshkumar et al. (2023)	The adoption barriers to Industry 4.0 (I4.0) technologies in farmer-producers	Not specified	Modeling	Interpretive structural modeling (ISM)	India
Georgopoulos et al. (2023)	Factors influencing the adoption of AI technologies in agriculture	Not specified	Literature reviews	N/A	N/A
Mishra et al. (2023)	Challenges to AI in the agricultural sector during the COVID-19 pandemic	Not specified	Surveys and modeling	ISM	India
Puppala et al. (2023)	Barriers to the adoption of unmanned aerial vehicles for precision agriculture	Not specified	Modeling	Fuzzy Delphi and Fuzzy analytic hierarchy process (AHP)	India
Silveira et al. (2023a)	Barriers that hinder the implementation of Agriculture 4.0	Not specified	Literature reviews and modeling	Confirmatory factor analysis	Brazil
Silveira et al. (2023b)	Modeling the barriers that hinder the development of Agriculture 4.0	Not specified	Literature reviews and modeling	ISM	Brazil

Continued

Table 1
(Continued)

Author(s) (year)	Topic focused	Theory adopted	Research methodology adopted	Modeling techniques used	Country focused
Adereti et al. (2024)	Barriers to machine learning-based intelligent agricultural decision support systems	Not specified	Surveys	N/A	USA
Ahmad et al. (2024)	Challenges to AI adoption in agriculture in developing nations	Not specified	Literature reviews	N/A	Not specified
Alexander et al. (2024)	Challenges to build trust in AI-enabled agriculture and food system technology	Not specified	Case studies/ interviews	N/A	USA
Brugler et al. (2024)	Identification of barriers to the adoption of decision support systems with machine learning	Not specified	Literature reviews	N/A	Not specified
Dibbern et al. (2024)	Drivers and barriers to the adoption of digital agriculture technologies	Not specified	Literature reviews	N/A	Not specified
Gardezi et al. (2024)	Challenges and opportunities for adoption of AI in farming	Not specified	Theoretical and conceptual	N/A	Not specified
Hasteer et al. (2024)	Challenges to implement AI in the agriculture sector	Not specified	Modeling	Modified total interpretive structural modeling (TISM)	India
Kaushik et al. (2024)	Modeling the challenges of technology adoption in dairy farming	TAM and unified theory of acceptance and use of technology	Modeling	Fuzzy ISM	India
Mallinger and Baeza-Yates (2024)	Challenges for using AI in farming	Socio-technological-environmental approach	Literature reviews	N/A	N/A

Continued

Table 1
(Continued)

Author(s) (year)	Topic focused	Theory adopted	Research methodology adopted	Modeling techniques used	Country focused
Rodzi et al. (2024)	Barriers hindering digital technology adoption in the agriculture sector	Not specified	Modeling	Decision-making trial and evaluation laboratory (DEMATEL)	Malaysia
Sood et al. (2024)	Key determinants of adopting AI in agriculture	Not specified	Literature reviews	N/A	N/A
Srinivasan and Yadav (2024)	Barriers to the adoption of smart agricultural technologies	Not specified	Modeling	TISM	India
Zhao et al. (2024a)	Barriers to I4.0 adoption to achieve agri-food supply chain sustainability	Grand theory	Case studies/interviews and modeling	Group-based fuzzy AHP	China
Achille and Velamuri (2025)	Barriers to the adoption of digital farming technology	Not specified	Case studies/interviews	N/A	Nigeria
Ajmera et al. (2025)	Challenges of the adoption of AI-enabled digital technologies in the food industry	Not specified	Modeling	Best-worst method	Not specified
Balasooriya and Sedera (2025)	Top management challenges in using AI	Technology-organization-environment framework	Case study/interviews	N/A	Australia
Erike et al. (2025)	A review of AI applications and challenges for precision agriculture	Not specified	Literature reviews	N/A	Not specified
Narayanamurthy et al. (2025)	Barriers to smart farming	Not specified	Surveys	N/A	India
Saha et al. (2025)	Digital technology adoption challenges in agri-food systems	Not specified	Surveys and modeling	Fuzzy-ISM-DEMATEL	India
Vahdanjoo et al. (2025)	Drivers and barriers to digital transformation of the agri-food system	Not specified	Literature reviews	N/A	N/A

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are inherent to AI-enabled digital technology adoption but often under-theorized in AI-focused literature. By synthesizing insights from these diverse perspectives, our analysis provides a comprehensive understanding of the challenges associated with adopting AI-enabled digital technologies in the agricultural sector.

2.4. Research gaps

Our narrative review highlights several research gaps that offer promising directions for future studies.

First, only a limited number of studies have employed theoretical frameworks to examine the challenges associated with the adoption of AI-enabled digital technologies in agricultural contexts. For example, among the 30 studies included in Table 1, five adopted a theoretical framework to guide their research, such as TAM and the theory of planned behavior (Mohr and Kuhl, 2021), TAM and UTAUT (Kaushik et al., 2024), the socio-technological-environmental approach (Mallinger and Baeza-Yates, 2024), grand theory (Zhao et al., 2024a), and the TOE framework (Balasooriya and Sedera, 2025). We assume that theoretical frameworks are rarely adopted for several reasons. First, as AI-enabled digital technologies are relatively new, the literature is dominated by theoretical, conceptual, and review papers. Second, the application of AI-enabled digital technologies in farming is inherently interdisciplinary, attracting research from both business and management as well as engineering and agricultural science perspectives, which has contributed to the limited use of established theoretical frameworks. Third, our review focused exclusively on journal papers, while other types of publications such as book chapters and conference proceedings were excluded, which may have led to the omission of some studies that employed theoretical frameworks. The use of theory is essential, as it provides a systematic lens to interpret complex phenomena and offers structured explanations for why and how these phenomena occur. This theoretical grounding not only enhances analytical rigor but also contributes to the development of a cohesive and cumulative body of knowledge. This study fills the gap by employing a TOE framework.

Second, existing studies tend to investigate the barriers/challenges to the adoption of smart agricultural technologies using a single research methodology. This methodological limitation restricts the ability to capture the multifaceted nature of the issue from diverse perspectives. Addressing this gap, our study adopts a multi-method approach by integrating case studies and modeling techniques, thereby offering a more comprehensive understanding of the adoption process.

Third, our review reveals a geographic concentration in the existing literature, with most studies focusing on countries such as Brazil, India, Serbia, and the United States, while China remains relatively underexplored. Notably, China's agricultural total factor productivity (TFP) has experienced an average annual growth of over 2% between 1971 and 2022, which is largely attributed to technological advancements and efficiency improvements. TFP is a widely accepted indicator for assessing how efficiently multiple inputs, such as labor, capital, land, fertilizers, seeds, water, and energy, are transformed into agricultural output. Recent findings by Ding and Gao (2025) underscore the role of AI as a catalyst in transforming China's agricultural sector, significantly enhancing the TFP of agricultural enterprises. Therefore, our investigation into the challenges surrounding the adoption

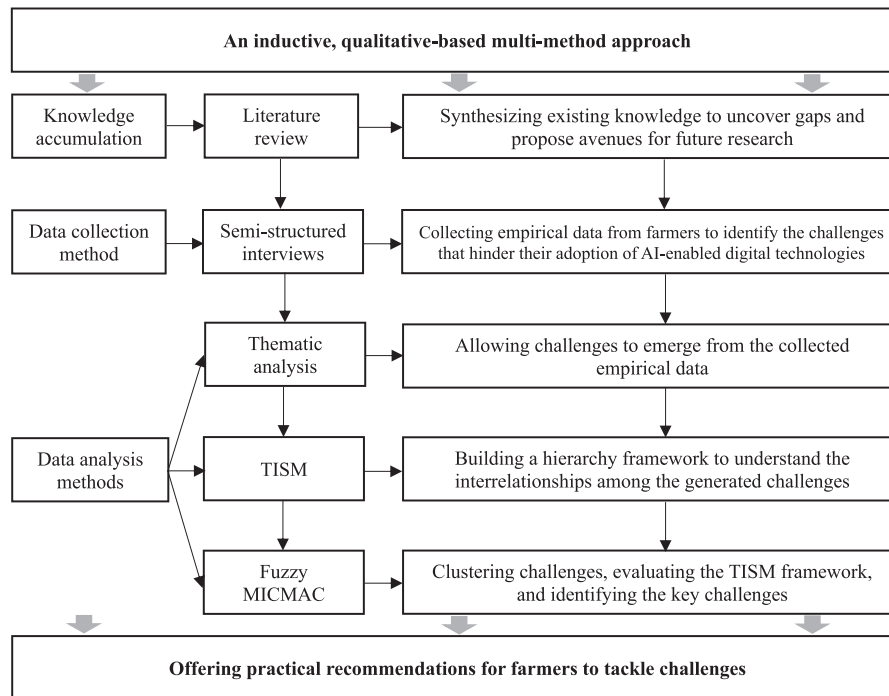


Fig. 1. Research methodology adopted.

of AI-enabled digital technologies in Chinese farms is not only timely but also critical. It has the potential to yield valuable insights and inform strategies that may be transferable to other countries facing similar challenges.

3. Research methodology

This study employs a multi-method approach to explore the challenges that hinder the adoption of AI-enabled digital technologies on farms. We adopted this approach for several reasons. First, a multi-method approach is particularly useful to address the urgent questions arising from our modern transformational age (Gruber, 2023). Such transformational questions often require multi-level analysis and involve complex dynamics that are difficult to capture using a single methodology (Wellman et al., 2023). For example, while the application of AI in agriculture promises increased efficiencies, reduced operational costs, and improved environmental outcomes, its adoption rate remains very low (Omotayo et al., 2025). We believe that a range of challenges spanning environmental, technological, organizational, and individual levels impedes the adoption of AI-enabled digital technologies on farms. Second, a multi-method approach combines multiple qualitative or quantitative methods, thereby facilitating a more complete and accurate understanding of a phenomenon and generating new insights that are both theoretically and practically valuable (Daft and Lewin, 1990). It is widely considered as more effective in generating a deep and comprehensive understanding of a phenomenon than a mixed-method approach (Zhao et al., 2020). Third, we

adopt a multi-method approach because it is advantageous in balancing the limitations of individual methods and boosting both the internal and external validity of our findings (McGrath, 1981). For example, semi-structured interviews and thematic analysis are often criticized by scholars for their subjectivity and potential for bias (Nowell et al., 2017). To mitigate this issue, we adopted total interpretive structural modeling (TISM) and fuzzy cross-impact matrix multiplication applied to classification (MICMAC) to complement the limitations of the aforementioned methods and enhance our credibility.

Figure 1 illustrates the research methodology adopted, which includes literature reviews to lay a theoretical foundation and semi-structured interviews to collect empirical data from farmers, followed by three data analysis methods: thematic analysis to identify challenges, TISM to establish interrelationships among the identified challenges, and fuzzy MICMAC analysis to categorize the challenges into four distinct groups.

3.1. Data collection method

Semi-structured interviews are widely used to obtain subjective knowledge from individuals regarding a particular situation or phenomenon they have experienced (McIntosh and Morse, 2015). It was adopted in this study for several reasons. First, this study aims to gain a deep understanding of the challenges that hinder farmers from adopting AI-enabled digital technologies. Rich insights into this phenomenon can only be obtained through semi-structured interviews due to their flexibility in capturing detailed and in-depth qualitative data (Barriball and While, 1994). Second, a key advantage of semi-structured interviews is their high response rate, which is particularly appealing to academics compared to the often-low response rates associated with questionnaire surveys. Third, participants are encouraged to respond to open-ended questions outlined in the interview guide, and the researcher can probe their answers in further depth. This highly flexible framework constitutes the semi-structured aspect of this method, allowing previously unknown or unexpected information to emerge (O’Keeffe et al., 2016). However, such knowledge cannot be effectively obtained through unstructured or structured interviews, as the former lacks control over participants’ response and the latter strictly restricts participants to predefined areas of inquiry (Warren, 2002).

3.2. Data analysis methods

Following the semi-structured interviews, three data analysis methods were employed to ensure a comprehensive exploration of the collected data.

We first employed thematic analysis to allow themes to emerge from the collected data. Thematic analysis is a qualitative data analysis method for analyzing, organizing, describing, identifying, and reporting themes found within a dataset (Braun and Clarke, 2006). We employed it in this study for several reasons. First, it is a well-defined qualitative method with a structured process to follow. For example, Braun and Clarke (2006) and Nowell et al. (2017) proposed a six-step process to ensure a trustworthy and rigorous thematic analysis. Second, thematic analysis is widely applicable across various epistemologies and research questions. For example, Jayawickrama et al. (2016) employed thematic analysis to identify knowledge determinants in the implementation of the ERP system,

Zhao et al. (2024a) used it to identify barriers to adopting I4.0 for agri-food supply chain sustainability, and Zhao et al. (2025) applied it to explore supply chain knowledge mobilization barriers using qualitative data from Argentina. Third, thematic analysis is particularly useful for summarizing key features of a large dataset, exploring participant perspectives, highlighting similarities and differences, and uncovering unanticipated insights (King, 2004). Other frequently used qualitative data analysis methods were not suitable for this study due to their respective limitations. For example, content analysis is highly time-consuming and challenging to computerize, narrative analysis captures only a narrow range of perspectives, and discourse analysis does not yield definitive answers to specific research questions (Saunders et al., 2019).

Then, we employed TISM to establish interrelationships among the identified challenges by allocating them into different layers of a hierarchical framework. TISM, an advancement of interpretive structural modeling (ISM) (Sushil, 2012; Cipi et al., 2025), is a qualitative modeling technique that not only identifies the interrelationships among system elements but also provides interpretive insights into these linkages. Compared to ISM, TISM is considered more robust, as it facilitates deeper theoretical understanding by addressing the “what,” “why,” and “how” of the interconnections (Jena et al., 2017). Although several techniques can be employed to understand the relationships among different elements, each has limitations that render them less suitable for this study. For example, Decision-making trial and evaluation laboratory (DEMATEL) is effective in identifying cause–effect relationships among elements but is less applicable when dealing with problems relevant to challenges and uncertainties (Zhao et al., 2024b; Ferreira and Ferreira, 2026). Structural equation modeling (SEM) is a powerful multivariate statistical tool for testing and evaluating complex relationships and requires large sample sizes to produce reliable results. Wolf et al. (2013) suggested that SEM commonly requires between 30 and 460 cases. In contrast, TISM can be conducted with a smaller group of experts who qualitatively assess the relationships between elements. Last, while graph theory is useful for visualizing relationships between nodes and edges, it lacks capability to determine the directionality of relationships between variables (Agarwal et al., 2022).

Finally, we employed fuzzy MICMAC analysis to classify the variables into four distinct clusters and to identify the key driving variables within the system. MICMAC analysis is a widely adopted technique for evaluating the driving and dependence power of variables within a system, thereby facilitating the identification of those that significantly influence the system. While alternative techniques such as analytic hierarchy process (AHP), analytic network process (ANP), and BWM can also be used to determine key variables, each of these methods presents specific limitations that make them unsuitable for the context of this study. For example, AHP is effective for ranking multiple variables within a system by constructing a hierarchical structure; however, it becomes challenging to prioritize a large number of variables, as inconsistencies may arise in expert judgments when the number of comparisons increases (Mangla et al., 2018). ANP allows for the analysis of interdependencies among decision-making attributes and can help determine priorities in complex systems. Nevertheless, it has notable drawbacks, including a heavy reliance on expert opinion and increasing analytical complexity as more variables are introduced. Finally, despite BWM being useful for pairwise comparisons, it involves a complex calculation process and lacks the ability to determine a global optimal solution and was therefore not adopted in this study (Liang et al., 2020).

4. Empirical data collection

Empirical data refer to data obtained through observation and documentation of specific behaviors and patterns, or collected via experimentation, and can be either qualitative or quantitative (VandenBos, 2007; Adkins and Lury, 2009). In this study, we collected qualitative empirical data from Chinese farmers. Shandong Province, China, was selected as the site for our empirical data collection for several reasons. First, Shandong is one of China's leading producers and exporters of vegetables, renowned for both the superior quality and diversity of its produce. In 2023, the province's vegetable planting area reached 23.68 million mu, accounting for 6.9% of China's total, while its vegetable output totaled 92.72 million tons, equivalent to 11.19% of the national production (Zhao et al., 2023). Second, the province has seen widespread adoption of AI-powered digital technologies in vegetable production. These include AI-enabled robotic dogs for crop inspection, as well as electrified and smart greenhouse systems (People's Daily Online, 2025). Third, our strong professional ties with agricultural science scholars in Shandong, established through collaborative projects such as the EU Horizon 2020 Programme, facilitated access to key stakeholders and supported our fieldwork activities. Given that our study focuses on the challenges associated with adopting AI-enabled digital technologies in vegetable farming, these enabling conditions provide a valuable foundation for generating meaningful insights.

Two sampling techniques were employed to identify and select information-rich cases that are highly relevant to the phenomenon under investigation. First, we adopted purposive sampling, leveraging our existing connections with farms in Shandong Province to recruit suitable participants. To guide this process, three selection criteria were developed through a roundtable discussion with the scholars involved in the project: (1) the selected farms must be medium- or large-sized operations that have implemented AI-enabled digital technologies to support their agricultural activities; (2) the farms must be crop-focused, as this study specifically concentrates on vegetable farming; and (3) the participating farmers must have over 10 years of farming experience and possess a solid understanding of AI, digital technologies, and smart agriculture, ensuring a high level of expertise and professionalism. Drawing on our personal connections and our partner's local networks, we initially screened 26 crop farms across Shandong Province that were potentially willing to participate in the study. However, some of these farms were either small-scale operations with limited application of AI-enabled digital technologies or were unwilling to accommodate field visits. As a result, 12 farms met the criteria and were retained for further engagement. Subsequently, we disseminated information about the project through the farm's internal WeChat working groups, and in some cases, relied on recommendations from farm managers to identify and recruit interview participants. This process initially resulted in 18 participants. At the end of each interview, we employed a snowball sampling strategy by asking participants, "Do you know anyone who meets our selection criteria and might be interested in participating in this study?" Through this approach, an additional six participants were identified, bringing the total sample size to 24. Table 2 presents detailed information about the interview participants.

Before conducting the interviews, we developed an interview guide through a roundtable discussion with two experienced professors specializing in qualitative research. Based on this discussion,

Table 2
Interviewee's information

Farms	Main businesses	Interviewee (department and title)	Working experience (years)
1	Chinese leaf	Company director	18
		Director of technology management	10
2	Tomato	Founder of the farm	15
		Co-founder of the farm	14
3	Mixed vegetables	Director of quality management	12
		Director of pest management	14
4	Mixed vegetables	Director of maintenance	11
		Director of quality management	16
5	Mushroom	Director of technology management	15
		Director of human resource management	17
6	Mixed vegetables	Smart greenhouse operator	10
		Smart greenhouse operator	10
7	Mixed vegetables	Director of technology management	17
		Director of quality management	12
8	Cabbages	Director of pest management	14
		Director of planning	13
9	Onions and garlies	Director of technology and knowledge management	15
		Director of training and education	16
10	Mixed vegetable	Founder of the farm	22
		Director of technology management	16
11	Mixed vegetables	Director of pest management	14
		Director of quality management	18
12	Chinese leaf	Director of technology management	11
		Director of production management	16

the guide was structured into three main sections (see Appendix 1): Section 1 focused on gathering background information about the interviewees and their farms; Section 2 explored the current and planned adoption of AI-enabled digital technologies; and Section 3 concentrated on the challenges associated with adopting these technologies. To further validate the effectiveness of the interview guide, we conducted pilot interviews with three Chinese farmers. The pilot interviews revealed the need to include an additional question related to addressing environmental challenges and highlighted the importance of preparing a Chinese-language version of the interview guide to ensure clarity and accessibility. As a result, an additional question was incorporated: “What recommendations would you make to government bodies or industry stakeholders to tackle environmental challenges?” The interview guide was shared with participants via WeChat three days prior to the scheduled interviews, allowing sufficient time for them to prepare their responses. With participants’ consent, each interview was audio-recorded. Two Ph.D. students fluent in Chinese conducted the interviews, ensuring effective communication and cultural sensitivity. Throughout the interviews, probing questions were frequently employed to encourage participants to elaborate on or clarify their responses when necessary.

5. Data analysis and findings

This section outlines the steps involved in each data analysis method used in the study, including thematic analysis, TISM, and fuzzy MICMAC analysis.

5.1. Identifying challenges through thematic analysis

The qualitative data collected through semi-structured interviews were first analyzed using thematic analysis. This approach followed five key steps: transcribing, familiarizing, coding, categorizing, and reporting. Each interview audio file was transcribed verbatim to ensure that no important insights from participants were lost. The transcripts were then edited to remove irrelevant content, such as off-topic conversations, filler words, and repetitive or unclear segments that did not contribute meaningfully to the core discussion. Next, the cleaned transcripts were read multiple times to build familiarity with the data prior to open coding. During the open coding stage, data relevant to the challenges associated with the adoption of AI-enabled digital technologies in farming were coded inductively. This process was supported by NVivo 13, a qualitative data analysis software. Two Ph.D. students, who were also involved in the literature review, independently coded the transcripts to ensure reliability. Inter-coder reliability was assessed to determine the level of agreement between the two coders. The resulting score of 0.73 indicates a substantial level of agreement. According to the classification by Landis and Koch (1977), a score between 0.61 and 0.80 reflects substantial agreement, while scores between 0.81 and 1.00 indicate almost perfect agreement. This process ensured consistency and robustness in the coding of the qualitative data. The initial first-order codes were subsequently grouped into second-order themes, which were then further synthesized into aggregate dimensions. These themes and dimensions were labeled using established constructs drawn from both the TOE framework and the broader literature on AI adoption. An iterative approach was adopted throughout the coding and categorizing processes, moving back and forth between relevant theoretical insights and empirical data to refine both the codes (quotes from interview transcripts) and the themes (identified challenges). In particular, prior research on AI/I4.0 adoption challenges and digital transformation barriers in the agri-food sector (e.g., Costa et al., 2023) provided valuable insights, while empirical studies utilizing the TOE framework (e.g., Govindan, 2023) helped to interpret the data within this theoretical framework. This iterative process also enabled us to examine the relationships between codes and themes, as well as among themes and aggregate dimensions. Finally, the findings of this analysis were compiled into a comprehensive report (see Table 3).

Our thematic analysis identified 13 challenges hindering the adoption of AI-enabled digital technologies in farming, ranging from insufficient baseline data for modeling to the absence of a compatible technology ecosystem. While the traditional TOE framework categorizes such challenges into three dimensions, our findings revealed that individual-level factors also play a critical role. Specifically, interviewees consistently emphasized that farmers' knowledge, awareness, and skills are essential for successful adoption. Therefore, we extended the categorization to four dimensions: technology, organization, environment, and personal.

Table 3
Challenges to the adoption of AI-enabled digital technologies in Chinese farms

First-order codes	Second-order themes	Aggregate dimensions
<ul style="list-style-type: none"> “...its level of maturity still needs improvement.” “...the priority should be to develop simple, user-friendly, and fool-proof equipment that is easy to operate and accessible to a wider range of users.” 	Low maturity of AI-enabled digital technologies (T1)	Technology
<ul style="list-style-type: none"> “Another challenge that we face is the lack of complete baseline data for modelling.” “The absence of a standard, widely applicable measure of technological practicality hinders consistent adoption.” 	Insufficient baseline data for modeling (T2)	
<ul style="list-style-type: none"> “Because we lacked sufficient baseline data from the outset, the early models we developed, and the intelligent agricultural systems designed to manage crops were significantly limited in their accuracy and effectiveness.” 	Low accuracy and effectiveness of AI-enabled agricultural systems (T3)	
<ul style="list-style-type: none"> “...and large-scale production of the equipment has not yet achieved economies scale.” 	High cost of technology (T4)	
<ul style="list-style-type: none"> “The maintenance costs of AI-enabled digital technologies are relatively high.” 	High maintenance cost (T5)	
<ul style="list-style-type: none"> “The alignment of related fields such as pesticide application, requires a gradual and coordinated process.” “If a particular technology is highly advanced in one aspect but lacks a practical and compatible implementation pathway, its value becomes diminished.” 	Lack of a compatible technology ecosystem (T6)	
<ul style="list-style-type: none"> “...without a clear understanding of AI-enabled digital technology.” “As a result, there is a lack of a management culture that is rooted in, or driven by, digital technology.” 	Lack of digital technology management culture (O1)	Organization
<ul style="list-style-type: none"> “The cost and infrastructure required for adopting AI-enabled digital technologies are relatively high.” “...or farmers who have only recently started operations, financial constraints make it difficult to invest in such equipment.” 	Unclear about return on investment (O2)	

Continued

Table 3
(Continued)

First-order codes	Second-order themes	Aggregate dimensions
<ul style="list-style-type: none"> • “Another issue is the low level of soil standardization. For example, AI-enabled agricultural machinery often lacks the adaptability needed to operate effectively on different soil types, such as clay and sand.” 	Poor soil/farmland standardization (E1)	Environment
<ul style="list-style-type: none"> • “In the past, agricultural technology promotion departments served as a crucial intermediary, bridging advanced technologies with grassroots farming practices.” • “However, many of these agricultural technology stations now exist in name only, with their functions significantly weakened or absent.” 	Absence of effective intermediaries in promoting agricultural technology (E2)	
<ul style="list-style-type: none"> • “This support is not universally accessible but rather depends on personal relationships, which hinders the effective application and widespread adoption of technology.” 	Access to government subsidies often depends on <i>guanxi</i> (E3)	
<ul style="list-style-type: none"> • “Most current farmers are over 45 years old, with the average age around 55.” • “...their knowledge structure remains relatively limited, particularly in areas such as model application...” 	Farmer’s knowledge structure remains limited (I1)	Personal
<ul style="list-style-type: none"> • “Currently, farmers have limited understanding of the technology, which creates a psychological barrier...” • “When water and fertilizer are managed automatically and accurately, farmers may feel that the automated system does not provide the same care or attention to the plants as manual methods.” 	Psychological barrier in the application of technology (I2)	

5.2. Establishing interrelationships between challenges through TISM

The challenges identified through thematic analysis were utilized as inputs for the TISM analysis. These challenges were systematically allocated into different levels of a hierarchical framework to explore and understand their interrelationships. The implementation of TISM followed a structured nine-step process, which included:

1. Identification and definition of challenges for analysis: 13 challenges to the adoption of AI-enabled digital technologies in farms were identified and used as inputs to process TISM (see Table 3).
2. Definition of contextual relationships between identified challenges: The contextual relationship between two elements depends on the nature of the structure being analyzed. For example, when dealing with problems, opportunities, or objectives, the relationship might be defined as: element A causes/enhances/achieves element B. In the context of challenges, the relationship is interpreted as challenge A leads to or causes challenge B.
3. Interpretation of relationships between identified challenges: This step involves clarifying and interpreting the nature of the contextual relationships between challenges. To achieve this, three experts, each with over 30 years of experience collaborating with the agri-food industry and previously involved in the semi-structured interviews, were consulted. They were asked to evaluate the relationships between pairs of identified challenges. The majority opinion among the experts was adopted to determine whether a relationship existed. In cases where a relationship was confirmed, an additional interpretive question was posed: “In what way does challenge A leads to or causes challenge B?” This approach not only validated the presence of relationships but also provided deeper insights into the underlying mechanisms linking the challenges.
4. Interpretive logic of the pair-wise comparison: An interpretive logic-knowledge base was developed for a pairwise comparison of the 13 identified challenges. This resulted in a total of 156 (i.e., $13 \times 13 - 13 = 156$) rows in the knowledge base for implementing this study. For each pair, expert judgment was used to determine whether a contextual relationship exists. If a relationship was identified, it was marked as “Yes,” and a corresponding interpretive explanation was provided to elaborate on how one challenge leads to or causes the other. If no relationship was identified, it was marked as “No,” and no further interpretation was required.
5. Reachability matrix and transitivity check: An initial reachability matrix was constructed based on the interpretive logic-knowledge base by assigning a value of “1” for each pair of challenges where a relationship was identified (“Yes”) and “0” where no relationship was found (“No”) (see Appendix 2). This initial matrix was then evaluated for transitivity, a fundamental principle in TISM. According to the transitivity rule, if challenge A is related to challenge B, and challenge B is related to challenge C, then it is inferred that challenge A is also related to challenge C. The matrix was updated iteratively to reflect all such transitive relationships until full transitivity was achieved, resulting in the final reachability matrix (see Table 4).
6. Level partition of the reachability matrix: The final reachability matrix was utilized to determine the hierarchical level of each identified challenge through iterative level partitioning. This process involved calculating the reachability set (all challenges that can be reached from a given challenge) and the antecedent set (all challenges that lead to a given challenge) for each challenge. The intersection set of these two was then used to assign levels. Challenges for which the reachability and intersection sets were identical were placed at the topmost level in that iteration. This process was repeated until levels were assigned to all challenges. The detailed partitioning process is illustrated in Appendix 3.
7. Development of the digraph: For visualization purposes, the 13 challenges to the adoption of AI-enabled digital technologies were represented using a digraph. In this digraph, direct links between challenges were drawn according to the relationships established in the final reachability.

Table 4
Final reachability matrix

	T1	T2	T3	T4	T5	T6	O1	O2	E1	E2	E3	I1	I2
T1	1	1*	1	1*	1	1	0	1*	0	0	0	0	1*
T2	1	1	1	1*	1*	1*	0	1*	0	0	0	0	1*
T3	0	0	1	0	0	1	0	0	0	0	0	0	1
T4	1*	1	1*	1	1*	1*	0	1	0	0	0	0	1
T5	1*	1*	1*	1	1	1*	0	1*	0	0	0	0	1
T6	0	1	0	0	1	1	0	0	0	0	0	0	0
O1	1*	1	1*	1*	1*	1	1	0	0	0	0	0	1
O2	0	0	0	0	0	1	0	1	0	0	0	0	1
E1	0	0	1	0	0	0	0	0	1	0	0	0	1*
E2	1*	1	1	1	1*	1	1	1	0	1	0	1	1
E3	1	1	1	1	1	1	0	1*	1	0	1	0	1*
I1	1*	1*	1*	1*	1*	1*	1	1	0	0	0	1	1
I2	0	1	0	0	0	0	0	0	0	0	0	0	1

To distinguish between direct and transitive links, dotted lines were used to represent significant transitive links, those derived from the application of transitivity rather than direct expert input.

8. Development of the interaction matrix: The final digraph was translated into a binary interaction matrix, where all identified interactions between challenges were represented by entries of “1.” Each cell containing a “1” indicates the presence of a relationship between the corresponding pair of challenges. These interactions were then interpreted by referencing the relevant interpretations from the interpretive logic-knowledge base.
9. A total interpretive structural model of challenges: The TISM model of challenges was developed by integrating both the connective and interpretive information derived from the interpretive direct interaction matrix and the digraph. Each link within the model is accompanied by its corresponding interpretation, positioned alongside the respective connections. This leads to a total interpretation of the structural model encompassing both the nodes (challenges) and the links (relationships), thereby offering a comprehensive understanding of the hierarchical and causal structure among the identified challenges.

Our analysis of the challenges led to the development of a TISM hierarchical model comprising six levels (see Fig. 2). At the base of the hierarchy lies the absence of effective intermediaries in promoting agricultural technology (E2), whereas the top level is occupied by the lack of a compatible technology ecosystem (T6) and psychological barrier in the application of technology (I2). The remaining challenges are distributed across Levels II to V. Farmer’s knowledge structure remains limited (I1), primarily due to the lack of accessible and diverse channels for acquiring up-to-date knowledge. One interviewee stated that “*Currently, our most pressing challenge is the need to improve the overall quality of growers. In recent years, many young people have migrated to urban areas for work, leaving behind an aging farming population. This demographic tends to struggle with adopting new knowledge and technologies. While limited training available, their limited educational background and deeply rooted beliefs make it difficult for them to embrace change.*” The aging farming population, coupled with their limited knowledge structure, has contributed to the absence of a digital technology management culture (O1) in most farming organizations and

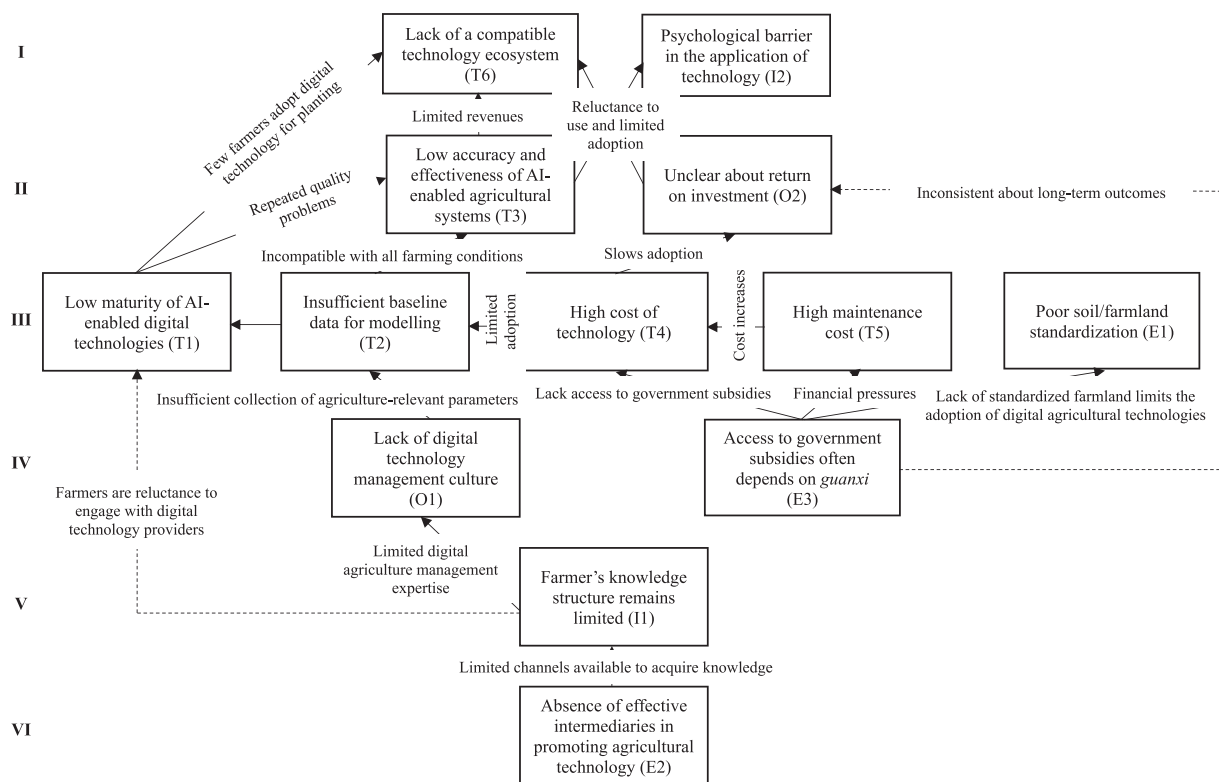


Fig. 2. TISM model of challenges.

agricultural parks. One interviewee highlighted that “*The knowledge and technological competencies of managers are often insufficient, leading to a significant cognitive gap. Many farms operate primarily from a capital-driven perspective, lacking both an understanding of digital technologies and a culture that supports digital technology-based management.*” The lack of a digital technology management culture (O1), combined with the reliance on *guanxi* (E3) for accessing government subsidies, has led to a range of technological and environmental challenges. These include the low maturity of AI-enabled digital agricultural technologies (T1), insufficient baseline data for modeling (T2), high technology costs (T4), high maintenance expenses (T5), and poor soil and farmland standardization (E1). Farmers are still in the early stages of adopting AI-enabled digital agricultural technologies. One major limitation is the insufficient availability of baseline data, as agriculture is a subject that involves numerous environmental changes over extended periods. Consequently, the initial models integrated into these digital technologies often lack the accuracy and reliability needed for decision-making. Farmers often criticize the quality of such technologies, pointing to their limited precision and practical utility. For example, in the case of AI-enabled automated precision water and fertilizer management systems, many farmers found the automatic irrigation function inadequate and chose to revert to manual operation. Moreover, the significant investment required to adopt AI-enabled digital agricultural technologies leaves many farmers uncertain about the return on investment (O2). This uncertainty has led to limited willingness among farmers to

adopt such technologies. As a result, technology manufacturers face constrained revenue streams, hindering their ability to further develop and sustain a robust technology ecosystem.

5.3. Clustering challenges through fuzzy MICMAC analysis

In the TISM analysis of challenges to the adoption of AI-enabled digital agricultural technologies, we used binary values, such as “0” and “1” to represent the relationships between challenges. A value of “1” indicates the presence of a relationship, while “0” denotes its absence. However, this binary approach has been criticized for its lack of accuracy (Yadav and Barve, 2016; Zhao et al., 2024c), as it fails to account for the varying strength of relationships, some of which may be weak, strong, or particularly strong. To address this limitation and enhance the sensitivity of our analysis, we applied fuzzy MICMAC analysis to evaluate the TISM model and classify the challenges more effectively. The development of the fuzzy MICMAC analysis involves three key steps.

1. Development of the binary direct relationship matrix: A binary direct relationship matrix was constructed by setting the diagonal entries to zeros and disregarding transitivity links present in the final reachability matrix of the identified challenges.
2. Construction of the fuzzy direct relationship matrix: Fuzzy set theory was employed to assess the strength of relationships between identified challenges on a scale ranging from 0 to 1, where: no relationship = 0, very low = 0.1, low = 0.3, medium = 0.5, high = 0.7, very high = 0.9, and complete = 1. Experts who participated in the TISM analysis were asked to evaluate the strength of relationships between each pair of challenges. Based on their judgments, these fuzzy values were superimposed onto the binary direct relationship matrix to develop the fuzzy direct reachability matrix (see Appendix 4).
3. Generation of fuzzy MICMAC stabilized matrix: We adopted the principle of fuzzy matrix multiplication proposed by Kandasamy et al. (2007) to guide the iterative multiplication process and achieve a stabilized matrix. Fuzzy matrix multiplication is essentially a generalization of Boolean matrix multiplication. According to fuzzy set theory, the outcome of two fuzzy matrices results in another fuzzy matrix. This multiplication is repeated until the values of driving power and dependence power reach a stable state. Driving power and dependence power are calculated by summing the interaction values across rows and columns, respectively. The formula used for fuzzy matrix multiplication is presented as follows:

$$C = A, B = \max_k (\min (a_{ik}, b_{kj})) , \text{ where } A = [a_{ik}] \text{ and } B = [b_{kj}]$$

We then used the MATLAB to perform the matrix calculations based on the aforementioned multiplication rule, resulting in a stabilized matrix, as presented in Table 5. Driving power refers to a challenge’s ability to influence or trigger other challenges; challenges with higher driving power exert greater influence across the system. Dependence power, on the other hand, indicates the extent to which a challenge relies on other challenges to be achieved; challenges with higher dependence power are more reliant on the resolution of others.

Table 5
The fuzzy MICMAC stabilized reachability matrix

	T1	T2	T3	T4	T5	T6	O1	O2	E1	E2	E3	I1	I2	Driving power
T1	0	0.5	0.7	0.7	0.7	0.7	0	0.7	0	0	0	0	0.7	4.7
T2	0.7	0	0.7	0.7	0.7	0.7	0	0.7	0	0	0	0	0.7	4.9
T3	0.3	0.3	0	0.3	0.3	0.3	0	0.3	0	0	0	0	0.5	2.3
T4	0.5	0.5	0.5	0	0.5	0.7	0	0.7	0	0	0	0	0.7	4.1
T5	0.5	0.5	0.5	0.7	0	0.7	0	0.7	0	0	0	0	0.7	4.3
T6	0.3	0.3	0.3	0.3	0.3	0	0	0.3	0	0	0	0	0.3	2.1
O1	0.7	0.7	0.7	0.7	0.7	0.7	0	0.7	0	0	0	0	0.7	5.6
O2	0.3	0.3	0.3	0.3	0.3	0.7	0	0	0	0	0	0	0.7	2.9
E1	0.3	0.3	0.7	0.3	0.3	0.3	0	0.3	0	0	0	0	0.5	3
E2	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0	0	0	0.5	0.7	6.8
E3	0.7	0.5	0.7	0.7	0.7	0.7	0	0.7	0.5	0	0	0	0.7	5.9
I1	0.5	0.5	0.5	0.5	0.5	0.7	0.5	0.5	0.7	0	0	0	0.7	5.6
I2	0.3	0.3	0.3	0.3	0.3	0.3	0	0.3	0	0	0	0	0	2.1
Dependence power	5.8	5.4	6.6	6.2	6	7.2	1.2	6.6	1.2	0	0	0.5	7.6	

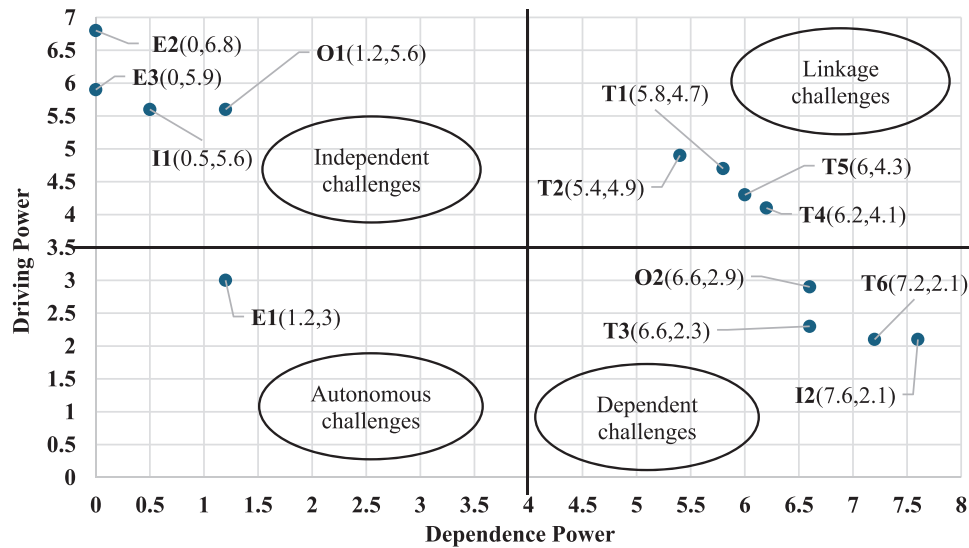


Fig. 3. Classification of challenges.

Figure 3 illustrates the classification of 13 challenges based on their respective driving and dependence power. These challenges are grouped into four distinct clusters: independent, linkage, dependent, and autonomous.

Independent challenges are characterized by high driving and low dependence power. They typically appear at the lowest level in the TISM hierarchy model. This cluster includes challenges such as the absence of effective intermediaries in promoting agricultural technology (E2), farmer's knowledge structure remains limited (I1), lack of a digital technology management culture (O1), and access to government subsidies often depends on *guanxi* (E3). These challenges serve as foundational drivers, influencing and enabling the emergence of other challenges within the system. For example, reliance on *guanxi* to access to government subsidies (E3) is a widespread cultural issue in China, which can trigger other challenges such as the high cost of technology adoption, elevated maintenance expenses, and inadequate standardization of soil and farmland. More specifically, many Chinese farmers depend heavily on government investment to develop high-standard farmland, making it essential for them to establish and maintain relationships with key government officials. Since *guanxi* is rooted in cultural norms, access to government subsidies often depends on *guanxi* (E3), which is not triggered by other challenges within the system but instead acts as a driver influencing others, making it an independent challenge.

Dependent challenges, such as unclear about return on investment (O2), low accuracy and effectiveness of AI-enabled agricultural systems (T3), lack of compatible technology ecosystem (T6), and psychological barriers in the application of technology (I2), are characterized by high dependence power and low driving power. These challenges typically occupy the highest level in the TISM hierarchy, as they are outcomes influenced by multiple other challenges rather than acting as initiators themselves. For example, AI-enabled digital agricultural technologies are often criticized by farmers for their lack of accuracy and effectiveness. This is primarily because AI systems cannot account for all agricultural conditions, and the models they rely on require the accumulation of

multi-parameter data over many years to perform reliably. Some farmers may initially express confidence in using AI-enabled digital agricultural technologies, but over time, their trust may diminish due to persistent issues with accuracy and effectiveness.

Linkage challenges are characterized by both high driving and high dependence power, typically positioned at the intermediate levels of the TISM hierarchy. In this study, four linkage challenges were identified as critical connectors between independent and dependent challenges: low maturity of AI-enabled digital technologies (T1), insufficient baseline data for modeling (T2), high cost of technology (T4), and high maintenance cost (T5). These factors jointly influence the adoption of AI-enabled agricultural technologies, as most farmers demonstrate low willingness to adopt them due to the significant costs involved and the perceived immaturity of the technologies.

Autonomous challenges are characterized by low driving and dependence power. These challenges are generally isolated within the system and have a minimal influence on or interaction with other challenges. In this study, only one autonomous challenge was identified: poor soil and farmland standardization (E1). As shown in the TISM hierarchy model, this challenge exhibits limited connections with other challenges in the system, reinforcing its autonomous nature.

6. Discussion

In this section, we compare our findings with existing literature to highlight our contributions to both academic knowledge and managerial practice. We then discuss the limitations of our study and propose directions for future research.

Our findings identify 13 challenges to the adoption of AI-enabled digital technologies on farms. Although many of these have been recognized in existing literature, we also uncover several novel challenges. Therefore, the first contribution of this study is the identification of adoption challenges that have received limited attention in prior research, such as reliance on *guanxi* for accessing government subsidies, poor soil and farmland standardization, insufficient baseline data for modeling, and the absence of effective intermediaries in promoting agricultural technologies. For example, Srinivasan and Yadav (2024) describe cultural barriers as a lack of awareness and education. Our study offers a different perspective that cultural issues in our context are more deeply rooted in social practices, particularly the reliance on *guanxi*, which can influence access to government subsidies. This highlights how cultural barriers can manifest differently across regions and agricultural systems. Costa et al. (2023) identified 12 barriers to the adoption of I4.0 technologies in the agricultural sector, including a lack of government support, psychological resistance, unreliability of specific technologies, and unstable Internet services. Our findings align with their study in several areas, particularly regarding farmers' reluctance to adopt advanced technological innovations and concerns about the reliability of certain high-sensitivity technologies. However, our study also reveals notable differences. In our context, government support for the adoption of advanced technologies is evident, and Internet infrastructure is generally reliable, indicating that these factors do not pose significant barriers. Compared with prior studies, our findings highlight context-dependent challenges that are deeply rooted in China's agricultural ecosystems, thereby offering novel insights.

The hierarchical organization of challenges into different layers of a framework constitutes an additional contribution, enabling us to identify key challenges and reveal their contextual interdependencies. Our findings highlight the absence of effective intermediaries in promoting agricultural

technology as a key challenge that warrants critical attention. At present, Chinese farmers primarily rely on two channels to obtain information about digital agricultural technologies: technology manufacturers and agricultural research institutes. However, both channels are limited in effectively promoting agricultural technology. Farmers often distrust technology manufacturers, as they tend to promote only their own AI-enabled digital technologies. While agricultural research institutes excel in research, they are less effective in providing knowledge and technology extension services. For example, they are often criticized for producing work that is “*very theoretical and disconnected from reality*.” Although these institutes offer technology and knowledge extension services, there is frequently tension between researchers and extension personnel, with each side blaming the other for shortcomings. Government-owned agricultural technology and skill extension stations are widely established; however, in practice, many exist in name only. As one interviewee noted: “*We used to have an intermediary called the agricultural technology and skills extension department, which connected technology providers with farmers. But now, these agricultural technology and skills extension stations exist in name only.*” This perspective contrasts with most existing studies, which identify financial constraints (Ganeshkumar et al., 2023), insufficient information about technologies and incompatibility with traditional farming practices (Chanchaichujit et al., 2024), and a lack of government support, incentives, and clear policies or protocols (Kumar et al., 2021) as the most critical barriers. These differences may be attributed to the socio-economic and policy environments of the country under investigation. Since 2004, the Chinese government has addressed farmers’ and rural-related issues through its annual “No. 1 Central Document,” signaling the central government’s priority on these matters. More recently, the government has strongly promoted the integration of AI into agriculture, focusing on areas such as precision farming, smart irrigation, and drone-based crop management (Li, 2025). To facilitate the adoption of advanced agricultural technologies, China has also implemented large-scale training and education programs for a new generation of farmers to support the modernization of agriculture, beginning with the 13th Five-Year Plan (The State Council, 2020). These policies and support measures have shaped the unique set of key challenges in China, differentiating them from those faced in other countries when adopting AI-enabled digital agricultural technologies. Regarding the interconnections between different challenges, our findings also demonstrate novelty. For example, Silveira et al. (2023b) argued that problems in education may lead to a lack of digital skills. By contrast, our findings suggest that the absence of effective intermediaries’ limits farmers’ knowledge. The former reflects the Brazilian context, where large-scale education and training opportunities are limited, whereas the latter reflects the Chinese context, where more practical, hands-on education, and training are required. According to the latest data from The State Council (2020), China has trained a total of five million high-quality farmers, directly developed 110,000 rural practical talent leaders and, for the first time, expanded enrolment in agriculture-related higher vocational education for farmers by 35,000. It is expected that more individuals will receive relevant training and education as China allocates increasing financial resources to agricultural modernization. Srinivasan and Yadav (2024) suggested that cultural barriers may lead to ineffective policy and regulation implementation and weak institutional support. Our study does not support this claim in the Chinese context. China’s hierarchical cultural value orientation emphasizes fulfilling obligations within a hierarchical system (Schwartz, 2006), which ensures that central government policies and regulations are effectively implemented. The second contribution of this study lies in developing a hierarchical framework of challenges, identifying key challenges, and explaining their

interrelationships through contextualized knowledge, thereby providing in-depth insights into why these challenges arise in the adoption of AI-enabled digital technologies in Chinese farms.

Finally, our classification of challenges into four distinct clusters presents a novel contribution to existing literature, as it enables us to distinguish between root causes and consequential effects. It indicates that environmental challenges, which are deeply embedded in external cultural and policy contexts, can drive challenges at the individual, organizational, and technological levels. Consequently, environmental challenges such as the absence of effective intermediaries for promoting agricultural technology and the reliance on *guanxi* to access government subsidies exhibit the highest driving power and function as independent challenges. For example, in China, AI-enabled digital technologies are typically adopted by farms with more than 200–300 hectares of farmland, as these technologies are expensive. These large farms depend heavily on government subsidies, which serve as an effective tool for achieving national food security and providing income support (Li et al., 2022). Consequently, building and maintaining *guanxi* with key government officials becomes critical for them. Even small- and medium-sized farms, they also need to cultivate *guanxi* with officials, as they operate in a hierarchical cultural environment. Although China has established agricultural technology extension hubs across the country, they now largely exist in name only. As noted by one of our interviewees: “*For technical services and the application of technical equipment, such an intermediary link is necessary. If it is not restored, agricultural extension will face great difficulties.*” Without appropriate intermediaries to promote agricultural technology, farmers may have limited knowledge and therefore limited opportunities to apply relevant technologies. The situation is further exacerbated by China’s reliance on imported AI-enabled digital technologies, which are often not well-suited to the country’s agricultural context. This mismatch has led to low accuracy and effectiveness, as well as the absence of a compatible technology ecosystem. Consequently, it is understandable that farmers develop psychological barriers, which emerge as one of the dependent challenges. Our classification of challenges differs from similar studies. For example, Silveira et al. (2023b) argued that technological, economic, and social barriers act as independent challenges, whereas political and environmental barriers serve as dependent challenges. Their findings contrast with ours because their study focused on Brazil, employed a different typology for classifying challenges, and did not apply a theoretical framework. Hasteer et al. (2024) shared a similar perspective with our study, suggesting that adverse climatic conditions and lack of skilled workforce function as independent challenges, whereas low precision and accuracy, reluctance to implement advanced technologies, and high costs operate as dependent challenges. We assumed that they identified adverse climatic conditions as an independent challenge because such conditions can directly damage AI equipment and undermine its effectiveness. This differs from our context, as most AI equipment in China is deployed in intelligent greenhouses, which are protected by glass structures. Senna et al. (2022) identified lack of knowledge and lack of interoperability capability as linkage challenges, whereas the need for high-level investments was categorized as a dependent challenge. Our study partially supports their argument, as we found that technology-related challenges such as insufficient baseline data for modeling function as linkage challenges that negatively influence farmers’ user experience. This issue arises because most AI-enabled digital technologies are imported from other countries, where the AI models were trained on foreign datasets that may not align with China’s agricultural context. The next contribution of this study is the classification of the 13 identified challenges according to their driving and dependence power,

along with an interpretation of these classifications within China's socio-cultural and technological context.

6.1. Theoretical contributions

The TOE framework has been widely applied in the literature to examine the adoption of technological innovations across various contexts. For example, Malik et al. (2021) explored factors influencing blockchain technology adoption in the Australian context, Shahadat et al. (2023) investigated digital technology adoption in SMEs within emerging economies, and Yin (2023) examined the relationship between digital transformation and green innovation using the TOE framework. While the TOE framework has been extensively used to understand technology adoption across different disciplines and settings, its application in investigating the adoption of AI-enabled digital technologies within the farming sector remains limited. This study takes an important initial step in addressing this gap by reorganizing the traditional TOE framework into a P-TOE framework and highlighting the critical role of specific knowledge and technical skills in the adoption of AI-enabled digital technologies in agricultural contexts. Specifically, this study identifies two key individual-level challenges: the limited knowledge structure of farmers and psychological barriers to technology application. As such, we reorganize the traditional TOE framework into a P-TOE framework, where the “P” dimension stands for “People” and captures individuals' experiences, knowledge, and skills. Experience refers to the accumulated exposure to situations, practices, and problem-solving in specific contexts (Kolb, 1984). Knowledge represents familiarity, awareness, or understanding of a subject (Nonaka and Takeuchi, 1995), while skills are practical capabilities that enable individuals to effectively apply knowledge in practice (Boyatzis, 2008). Previous theoretical frameworks have also incorporated individual-level factors that influence the adoption of digital technologies in agriculture. For example, Mohr and Kuhl (2021) applied TAM and the theory of planned behavior to examine the acceptance of AI in German agriculture, finding that personal attitude, perceived behavioral control, and personal innovativeness significantly shape AI adoption. Kaushik et al. (2024) combined TAM and UTAUT to model challenges of technology adoption in dairy farming but only considered one individual-level factor: low awareness. Mallinger and Baeza-Yates (2024), adopting a socio-technological-ecological approach, emphasized limited farmers access to knowledge as a social challenge. Similarly, Balasooriya and Sedera (2025) used the TOE framework to explore top management challenges in adopting AI in Australian agribusiness. While they identified resistance to change and limited knowledge/expertise as individual-level challenges, these were classified as organizational and technological barriers, respectively. Saad et al. (2024) developed a model of IoT adoption determinants using the TOE framework; however, individual-level factors were clearly overlooked in their analysis. Although prior studies have recognized various individual-level factors that hinder the adoption of digital technologies in agricultural, such factors have not been explicitly represented within the theoretical frameworks applied. Given that individuals are playing an increasingly important role in applying digital technologies, overlooking individual-level factors may result in an incomplete understanding of adoption challenges. Therefore, explicitly incorporating individual-level challenges into the analysis provides a more holistic perspective that complements technological, organizational, and environmental dimensions. Thus,

we reorganized the traditional TOE framework into a P-TOE framework by explicitly adding the personal (P) dimension.

6.2. Managerial contributions

Our study also provides practical managerial implications for farmers, technology manufacturers, and governments, aimed at facilitating the adoption of AI-enabled digital technologies in agriculture.

Regarding managerial implications for farmers, we suggest that they should actively engage in networking or building *guanxi* with key government officials who hold authority over resource (e.g., subsidies) allocation. Although subsidies are formally available to support the adoption of AI-enabled digital technologies, access is frequently shaped by personal connections (*guanxi*) rather than solely by objective eligibility criteria. This may be attributed to China's hierarchical cultural environment (Schwartz, 2006), in which governance is structured across multiple levels of government that hold considerable authority in resource allocation. Moreover, in this cultural environment, social power, obedience, and wealth are highly valued, while competition is viewed positively. Consequently, it is not surprising that individuals seek to establish relationships with key government officials. Our TISM and fuzzy MICMAC analysis further indicate that access to government subsidies often depends on *guanxi*, which emerges as an independent challenge not influenced by other challenges in the system. Practical measures for building *guanxi* with government officials include participating in official events such as training workshops, inviting local officials to visit farms during demonstration days, and aligning farm's activities with government priorities.

Regarding managerial implications for technology manufacturers, we suggest that they should enhance AI-enabled digital agricultural technologies by improving their effectiveness and accuracy, while also reducing costs, including maintenance expenses. In this study, we identified six challenges within the technological dimension. These challenges arise for several reasons. First, China relies heavily on smart agricultural technologies imported from countries such as France, the Netherlands, Israel, and Japan, as confirmed by our interviewees: “*In recent years, many technologies have mainly been introduced from Europe (France and the Netherlands), Israel, and also from neighbouring countries such as Japan.*” However, these technologies are often not well-suited to the Chinese agricultural context, as the underlying AI models are trained on foreign datasets. Second, while some domestic manufacturers have developed AI-enabled digital agricultural technologies tailored to local conditions, the AI models remain underdeveloped due to insufficient training data: “*Therefore, during the 11th Five-Year Plan period, we also put information and automation management in this area on the agenda. In fact, we have only just started in this regard.*” Third, as AI-enabled digital technologies are still emerging, they have yet to achieve economies of scale, resulting in high acquisition and maintenance costs. Therefore, we suggested several practical measures to tackle these challenges including (1) continuously refining AI models and improving technology performance through the collection and analysis of farm usage data; (2) designing equipment and software that can be upgraded or customized without replacing entire systems; (3) building partnerships with local technicians or agri-tech consultants to provide on-the-ground support and training; (4) introducing leasing, subscription, or pay-per-use models to reduce upfront cost barrier for farmers; and finally (5) given that the majority of Chinese farmers are over 50 years old and often face

difficulties in acquiring new knowledge or adapting to emerging technologies, it is essential to develop interfaces that are intuitive, ensuring that these technologies are easy to adopt and operate.

Regarding managerial implications for Chinese governments, we offer several practical suggestions. First, Chinese governments currently allocate subsidies to farmers based on farmland area, a practice that has been widely criticized for potentially favoring those with strong *guanxi* with key government officials rather than distributing support solely based on objective criteria. To mitigate this issue, we suggest that governments consider shifting subsidy allocation toward technology manufacturers, using performance-based metrics such as the number of units sold or adopted by verified farmers. This approach could ensure a more equitable distribution of resources and encourage manufacturers to promote adoption across a wider range of farming communities. Second, in China, technological services are currently delivered directly by technology manufacturers or agricultural research institutes. This fragmented approach may lead to distrust among farmers, as each manufacturer operates its own extension services, often promoting proprietary solutions. The situation can be further exacerbated when conflicts arise between farmers and technology manufacturers. Thus, we recommend governments establish non-profit agricultural technology extension hubs to support and accelerate the adoption of advanced technologies. Such hubs could serve as neutral intermediaries, connecting farmers with multiple manufacturers and offering unbiased guidance on the adoption of appropriate agricultural technologies. Third, given the vast scale of China and the dispersed nature of its farming population, to ensure that farmers across different regions have access to relevant and timely information, we suggest that governments develop digital platforms, such as traceability systems and supply-and-demand information platforms. These platforms can enhance real-time information sharing, promote transparency, and support better decision-making among farmers. Moreover, the implementation of such platforms offers a valuable opportunity to observe and assess farmers' responses to the adoption of AI-enabled digital agricultural technologies. Finally, the age profile of Chinese farmers presents a significant barrier to the adoption of AI-enabled digital technologies. As a result, traditional theory-based knowledge dissemination models may have limited effectiveness in this context. We recommend governments adopt practical, hands-on training programs tailored to this demographic. Demonstration-based learning, peer-to-peer mentoring, and field-based workshops can provide more accessible and relatable ways for older farmers to understand and engage with AI-enabled digital agricultural technologies.

6.3. Limitations and future research directions

This study is not without limitations. First, this study has a generalizability limitation, as the research was conducted solely within the context of China. We acknowledge that China's unique institutional and cultural characteristics may shape the adoption of AI-enabled digital technologies in agriculture. For example, China's cultural value orientation emphasizes hierarchy, which can encourage farmers to cultivate *guanxi* with government officials to access resources that support farm development. Consequently, access to government subsidies may depend on *guanxi*, presenting a contextual challenge that may not exist to the same extent in other countries. Future research could enhance external validity by examining whether the identified challenges, their interrelationships,

and their relative importance hold in other national or regional contexts through survey-based approaches. For example, comparative studies could investigate contexts with similar cultural value orientations, such as Thailand (Schwartz, 2006), or contrast them with countries (e.g., France) characterized by different institutional and cultural settings.

Second, this study employs TISM and fuzzy MICMAC analysis to explore the interrelationships among challenges and to determine their relative importance. Specifically, TISM was used to allocate the 13 identified challenges across different levels of a hierarchical framework, while fuzzy MICMAC analysis was subsequently applied to categorize these challenges based on their dependence and driving power. While these methods provide valuable insights by developing a hierarchical structure of challenges, they offered limited ability to capture the degree and direction of influence among the identified challenges. Future research could consider alternative multi-criteria decision-making techniques, such as fuzzy DEMATEL, to further examine the causal relationships between challenges and validate or refine the findings. DEMATEL is widely used to quantify both the strength and direction of influence among factors. For example, Feng et al. (2024) applied a DEMATEL-ISM-MICMAC approach to identify critical factors influencing digital innovation in manufacturing enterprises, while Susanty et al. (2025) employed DEMATEL and ISM to map barriers to digital adoption in micro and small enterprises. Integrating TISM, fuzzy MICMAC, and fuzzy DEMATEL could help balance the limitations of individual techniques, enhance theoretical rigor, and strengthen the explanatory power of future studies.

Third, our study does not track organizations over time and therefore cannot directly observe how changes in one challenge may influence others within the system. For example, although this study identifies the absence of effective intermediaries in promoting agricultural technologies as a key challenge, whether such an absence genuinely reshapes farmers' knowledge structures remains underexplored. Instead, this study relies on expert assessments to evaluate the interrelationships among challenges. Future research could adopt longitudinal research designs by embedding researchers within the managerial teams of farms that are willing to adopt AI-enabled digital technologies. Such approaches would enable researchers to observe how changes in one challenge trigger or reshape other challenges over time. Repeated observations and interviews with the same informants would provide deeper insights into the dynamic processes through which farmers navigate and overcome challenges associated with technology adoption. As noted by Ployhart and Vandenberg (2010), longitudinal approaches enable researchers to observe individuals over prolonged periods of time, which is particularly valuable for evaluating relationships among risk factors and for establishing sequence of events.

Finally, our study developed a hierarchical framework to understand the interrelationships among challenges using TISM and categorized these challenges through fuzzy MICMAC analysis. Since TISM and fuzzy MICMAC are widely regarded as qualitative techniques (Zhao et al., 2020), statistically verifying these interrelationships would further enhance the rigor and credibility of the study. Moreover, multi-level hierarchical models are often complex and may involve cyclical connections among factors. Accordingly, Yang et al. (2024) suggest transforming such hierarchical models into system dynamics causal loop diagrams to better capture feedback mechanisms. Future research could therefore employ system dynamics modeling to quantitatively validate these interrelationships. System dynamics modeling is a well-established methodology for modeling complex systems and quantifying complex feedback in system interactions (Forrester, 1994).

7. Conclusion

AI-enabled digital technologies remain a “blue ocean” of opportunity for farmers, characterized by high entry barriers but vast untapped potential. This study offers valuable insights into navigating this landscape by examining the challenges associated with adopting these technologies on farms. Our key findings differ from those of previous studies by emphasizing financial constraints, policy-related issues, and infrastructural deficiencies as the most critical challenges to adoption. In doing so, we make a unique contribution to the existing body of knowledge while addressing the three proposed research questions. First, this study identifies 13 challenges to the adoption of AI-enabled digital technologies on Chinese farms and categorizes them into four dimensions: personal, organizational, environmental, and technological. Amongst these challenges, several are novel to agri-food industry research and practice, such as poor soil and farmland standardization and the reliance on *guanxi* for accessing government subsidies. Second, we develop a hierarchical framework to uncover the interrelationships among these challenges, based on the premise that each challenge may have the potential to trigger others, albeit with varying degrees of influence. Third, while farmers face multiple challenges to adoption, it is essential to determine which challenges should be prioritized. Our findings reveal that the absence of effective intermediaries in promoting agricultural technologies plays a pivotal role in exacerbating other challenges within the system and thus should be addressed as a priority. Furthermore, the study reflects the reality that many medium- and large-sized farms in China, typically operating over 200 hectares of farmland, possess sufficient financial resources to adopt such technologies. However, adoption remains low primarily due to a lack of relevant knowledge and limited understanding of AI-enabled solutions rather than financial constraints alone. Although our study extends scholars’ understanding of the challenges associated with adopting AI-enabled digital technologies on farms, it also highlights actionable directions for future research. These include broadening the contextual scope, adopting longitudinal approaches, and employing mixed-method designs to further advance knowledge in this area.

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References

- Abbasi, R., Martinez, P., Ahmad, R., 2022. The digitalization of agriculture industry—a systematic literature review on agriculture 4.0. *Smart Agricultural Technology* 2, 100042.
- Achille, A.A., Velamuri, V.K., 2025. Drivers and barriers to the adoption of digital farming technology: evidence from Nigeria. *International Journal of Sustainable Agricultural Management and Informatics* 11, 3, 308–330.
- Addas, A., Tahir, M., Ismat, N., 2024. Enhancing precision of crop farming towards smart cities: an application of artificial intelligence. *Sustainability* 16, 1, 355.
- Adereti, D.T., Gardezi, M., Wang, T., McMaine, J., 2024. Understanding farmers’ engagement and barriers to machine learning-based intelligent agricultural decision support systems. *Agronomy Journal* 116, 3, 1237–1249.

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- Adkins, L., Lury, C., 2009. Introduction: what is the empirical? *European Journal of Social Theory* 12, 1, 5–20.
- Agarwal, N., Seth, N., Agarwal, A., 2022. Evaluation of supply chain resilience index: a graph theory based approach. *Benchmarking: An International Journal* 29, 3, 735–766.
- Ahmad, A., Liew, A.X.W., Venturini, F., Kalogeras, A., Candiani, A., Di Benedetto, G., Ajibola, S., Cartujo, P., Romero, P., Lykoudi, A., De Grandis, M.M., Xouris, C., Lo Bianco, R., Doddy, I., Elegbede, I., D’Urso Labate, G.F., García Del Moral, L.F., Martos, V., 2024. AI can empower agriculture for global food security: challenges and prospects in developing nations. *Frontiers in Artificial Intelligence* 7, 1328530.
- Aijaz, N., Lan, H., Raza, T., Yaqub, M., Iqbal, R., Pathan, M.S., 2025. Artificial intelligence in agriculture: advancing crop productivity and sustainability. *Journal of Agriculture and Food Research* 20, 101762.
- Ajmera, D., Kharub, M., Krishna, A., Gupta, H., 2025. Navigating the challenges of AI-enabled circular economy in the food and beverage sector: strategies for sustainable transformation. *The International Journal of Logistics Management* 36, 2, 611–646.
- Akkem, Y., Biswas, S.K., Varanasi, A., 2023. Smart farming using artificial intelligence: a review. *Engineering Applications of Artificial Intelligence* 120, 105899.
- Akpan, I.J., Kobara, Y.M., Owolabi, J., Akpan, A.A., Offodile, O.F., 2025. Conversational and generative artificial intelligence and human-chatbot interaction in education and research. *International Transactions in Operational Research* 32, 3, 1251–1281.
- Alexander, C.S., Yarborough, M., Smith, A., 2024. Who is responsible for ‘responsible AI’?: navigating challenges to build trust in AI agriculture and food system technology. *Precision Agriculture* 25, 146–185.
- Awa, H.O., Ojiabo, O.U., 2016. A model of adoption determinants of ERP within T-O-E framework. *Information Technology & People* 29, 4, 901–930.
- Balasoorya, A., Sedera, D., 2025. Top management challenges in using artificial intelligence for sustainable development goals: an exploratory case study of an Australian agribusiness. *Sustainability* 17, 15, 6860.
- Bang, R.N., Guajardo, M., Hansen, B.G., 2023. Recent advances in decision support for beef and dairy farming: modeling approaches and opportunities. *International Transactions in Operational Research* 30, 6, 2807–2839.
- Bao, J., Xie, Q., 2022. Artificial intelligence in animal farming: a systematic literature review. *Journal of Cleaner Production* 331, 129956.
- Barriball, L.K., While, A., 1994. Collecting data using a semi-structured interview: a discussion paper. *Journal of Advanced Nursing* 19, 328–335.
- Bohr, A., Memarzadeh, K., 2020. The rise of artificial intelligence in healthcare applications. In Bohr, A., Memarzadeh, K. (eds) *Artificial Intelligence in Healthcare*, Academic Press, Cambridge, MA, pp. 25–60.
- Boyatzis, R.E., 2008. Competencies in the 21st century. *Journal of Management Development* 27, 1, 5–12.
- Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. *Qualitative Research in Psychology* 3, 77–101.
- Brugler, S., Gardezi, M., Dadkhah, A., Rizzo, D.M., Zia, A., Clay, S.A., 2024. Improving decision support systems with machine learning: identifying barriers to adoption. *Agronomy Journal* 116, 3, 1229–1236.
- Camacho, J.M., Couce-Vieira, A., Arroyo, D., Insua, D.R., 2026. A cybersecurity risk analysis framework for systems with artificial intelligence components. *International Transactions in Operational Research* 33, 2, 798–825.
- Cao, A., Guo, L., Li, H., 2025. Understanding farmer cooperatives’ intention to adopt digital technology: mediating effect of perceived ease of use and moderating effects of interest usage and training. *International Journal of Agricultural Sustainability* 23, 1, 2464523.
- Chanchaichujit, J., Balasubramanian, S., Shukla, V., 2024. Barriers to Industry 4.0 technology adoption in agricultural supply chains: a fuzzy Delphi-ISM approach. *International Journal of Quality & Reliability Management* 41, 7, 1942–1978.
- Chittipaka, V., Kumar, S., Sivarajah, U., Bowen, J.L.-H., Baral, M.M., 2023. Blockchain technology for supply chains operating in emerging markets: an empirical examination of technology-organization-environment (TOE) framework. *Annals of Operations Research* 327, 465–492.
- Cipi, A., Ferreira, A.C., Ferreira, F.A.F., Ferreira, N.C.M.Q.F., 2025. Using interpretive structural modelling (ISM) to detect and define initiatives that facilitate hemodynamic laboratory management. *International Transactions in Operational Research* 32, 4, 2117–2138.

- Costa, F., Frecassetti, S., Rossini, M., Portioli-Staudacher, A., 2023. Industry 4.0 digital technologies enhancing sustainability: applications and barriers from the agricultural industry in an emerging economy. *Journal of Cleaner Production*, 408, 137208.
- Coulson, R.N., Folse, J.L., Loh, D.K., 1987. Artificial intelligence and natural resource management. *Science* 237, 4812, 262–267.
- Daft, R.L., Lewin, A.Y., 1990. Can organization studies begin to break out of the normal science straitjacket? An editorial essay. *Organization Science* 1, 1–9.
- Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13, 3, 319–340.
- Davison, R.M., Ou, C.X.J., Martinsons, M.G., 2018. Interpersonal knowledge exchange in China: the impact of guanxi and social media. *Information & Management* 55, 2, 224–234.
- Dibbern, T., Romani, L.A.S., Massruha, S.M.F.S., 2024. Main drivers and barriers to the adoption of digital agriculture technologies. *Smart Agricultural Technology* 8, 100459.
- Ding, M., Gao, Q., 2025. The impact of artificial intelligence technology application on total factor productivity in agricultural enterprises: evidence from China. *Economic Analysis and Policy* 86, 399–415.
- Dipierro, A.R., Witte, K.D., Toma, P., 2026. Nonparametric efficiency and artificial intelligence techniques in higher education: a systematic literature review and bibliometric analysis. *International Transactions in Operational Research* 33, 3, 1427–1464.
- Dissanayake, C.A.K., Jayathilake, W., Wickramasuriya, H.V.A., Dissanayake, U., Kopiyawattage, K.P.P., Wasala, W.M.C.B., 2022. Theories and models of technology adoption in agricultural sector. *Human Behavior and Emerging Technologies* 2022, 5, 9258317.
- Doluschitz, R., Schmisser, W.E., 1988. Expert systems: applications to agriculture and farm management. *Computers and Electronics in Agriculture* 2, 3, 173–182.
- Erike, A., Ikerionwu, C., Azubogu, A., Obodoagwu, V., 2025. Is AI for illiterate farmers? A systematic literature review of AI and machine learning applications and challenges for precision agriculture. *Discover Artificial Intelligence* 5, 204.
- Federal Reserve Bank of St. Louis., 2024. Contributions to percent change in real GDP by industry: manufacturing (CPGDPMA). FRED | St. Louis Fed. Available at <https://fred.stlouisfed.org/series/CPGDPMA> (accessed 15 September 2025).
- Feng, X., Li, E., Li, J., 2024. Critical factors identification of digital innovation in manufacturing enterprises: three stage hybrid DEMTEAL-ISM-MICMAC approach. *Soft Computing* 28, 7341–7361.
- Ferreira, N.C.M.Q.F., Ferreira, J.J.M., 2026. Integrating cognitive mapping, neutrosophic logic and DEMATEL for sustainable entrepreneurship in SMEs. *International Transactions in Operational Research* 33, 4, 2605–2638.
- Forrester, J.W., 1994. System dynamics, system thinking, and soft OR. *System Dynamics Review* 10, 2-3, 245–256.
- Ganeshkumar, C., Singh, N.K., Mor, R.S., Panghal, A., 2023. Investigating the adoption barriers to Industry 4.0 technologies in farmer producer organizations. *International Journal of Global Business and Competitiveness* 18, 162–174.
- Gardezi, M., Joshi, B., Rizzo, D.M., Ryan, M., Prutzer, E., Brugler, S., Dadkhah, A., 2024. Artificial intelligence in farming: challenges and opportunities for building trust. *Agronomy Journal* 116, 3, 1217–1228.
- Georgopoulos, V.P., Gkikas, D.C., Theodorou, J.A., 2023. Factors influencing the adoption of artificial intelligence technologies in agriculture, livestock farming and aquaculture: a systematic literature review using PRISMA 2020. *Sustainability* 15, 16385.
- Giua, C., Materia, V.C., Camanzi, L., 2022. Smart farming technologies adoption: which factors play a role in the digital transition? *Technology in Society* 68, 101869.
- Govindan, K., 2023. How digitalization transforms the traditional circular economy to a smart circular economy for achieving SDGs and net zero. *Transportation Research Part E: Logistics and Transportation Review* 177, 103147.
- Gruber, M., 2023. From the editors: an innovative journal during transformational times—embarking on the 23rd editorial term. *Academy of Management Journal* 66, 1–8.
- Hasteer, N., Mallik, A., Nigam, D., Sindhwani, R., Belle, J-P.V., 2024. Analysis of challenges to implement artificial intelligence technologies in agriculture sector. *International Journal of System Assurance Engineering and Management* 15, 1841–1860.
- Hemming, S., Zwart, F., Elings, A., Righini, I., Petropoulou, A., 2019. Remote control of greenhouse vegetable production with artificial intelligence—greenhouse climate, irrigation, and crop production. *Sensors* 19, 8, 1807.

- Holzinger, A., Saranti, A., Angerschmid, A., Retzlaff, C.O., Gronauer, A., Pejakovic, V., Medel-Jimenez, F., Krexner, T., Gollob, C., Stampfer, K., 2022. Digital transformation in smart farm and forest operations needs human-centered AI: challenges and future directions. *Sensors* 22, 3043.
- Iyer, L.S., 2021. AI enabled applications towards intelligent transportation. *Transportation Engineering* 5, 10083.
- Javaid, M., Haleem, A., Khan, I.H., Suman, R., 2023. Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochem* 2, 15–30.
- Jayawickrama, U., Liu, S., Smith, M.H., 2016. Empirical evidence of an integrative knowledge competence framework for ERP systems implementation in UK industries. *Computers in Industry* 82, 205–223.
- Jena, J., Sidharth, S., Thakur, L.S., Pathak, D.K., Pandey, V.C., 2017. Total interpretive structural modelling (TISM): approach and application. *Journal of Advances in Management Research* 14, 2, 162–181.
- Jha, K., Doshi, A., Patel, P., Shah, M., 2019. A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture* 2, 1–12.
- Kandasamy, W.V., Smarandache, F., Iianthenral, K., 2007. *Elementary fuzzy matrix theory and fuzzy models for social scientists*. Automaton, Los Angeles, USA.
- Kasemi, R., Lammer, L., Vincze, M., 2022. The gap between technology and agriculture, barriers identification and potential solution analysis. *IFAC-PapersOnline* 55, 39, 314–318.
- Kaushik, H., Rajwanshi, R., Bhadauria, A., 2024. Modelling the challenges of technology adoption in dairy farming. *Journal of Science and Technology Policy Management* 15, 6, 1455–1480.
- King, N., 2004. Using templates in the thematic analysis of text. In Cassell, C., Symon, G. (eds) *Essential Guide to Qualitative Methods in Organizational Research*. Sage, London, pp. 257–270.
- Kolb, D.A., 1984. *Experiential Learning: Experience as the Source of Learning and Development*. Prentice Hall, New Jersey.
- Kumar, S., Raut, R.D., Nayal, K., Kraus, S., Yadav, V.S., Narkhede, B.E., 2021. To identify industry 4.0 and circular economy adoption barriers in the agriculture supply chain by using ISM-ANP. *Journal of Cleaner Production* 293, 126023.
- Landis, J.R., Koch, G.G. 1977. The measurement of observer agreement for categorical data. *Biometrics*, 33, 159–174.
- Liang, F., Brunelli, M., Rezaei, J., 2020. Consistency issues in the best worst method: measurements and thresholds. *Omega* 96, 102175.
- Li, C., 2025. Artificial intelligence in Chinese agriculture: applications and prospects. Available at https://www.dcz-china.org/wp-content/uploads/2025/02/Study_AI-applications-in-agriculture_2025-01_FINAL.pdf (accessed 17 September 2025).
- Li, C., Sha, Z., Sun, X., Jiao, Y., 2022. The effectiveness assessment of agricultural subsidy policies on food security: evidence from China's poverty-stricken villages. *International Journal of Environmental Research and Public Health* 19, 21, 13797.
- Limpamont, A., Kittipanya-ngam, P., Chindasombatcharoen, N., Cavite, H.J.M., 2024. Towards agri-food industry sustainability: addressing agricultural technology adoption challenges through innovation. *Business Strategy and the Environment* 33, 7, 7352–7367.
- Luo, W., Zuo, S., Tang, S., Li, C., 2025. The formation of new quality productivity of agriculture under the perspectives of digitalization and innovation: a dynamic qualitative comparative analysis based on the “Technology-Organization-Environment” framework. *Sustainability* 17, 2, 597.
- Malik, S., Chadhar, M., Vatanasakdakul, S., Chetty, M., 2021. Factors affecting the organizational adoption of blockchain technology: extending the technology-organization-environment (TOE) framework in the Australian context. *Sustainability* 13, 16, 9404.
- Mallinger, K., Baeza-Yates, R., 2024. Responsible AI in farming: a multi-criteria framework for sustainable technology design. *Applied Sciences* 14, 437.
- Mangla, S.K., Luthra, S., Rich, N., Kumar, D., Rana, N.P., Dwivedi, Y.K., 2018. Enablers to implement sustainable initiatives in agri-food supply chains. *International Journal of Production Economics* 2023, 379–393.
- Marshall, A., Turner, K., Richards, C., Foth, M., Dezuanni, M., 2022. Critical factors of digital AgTech adoption on Australian farms: from digital to data divide. *Information, Communication & Society* 25, 6, 868–886.
- Marvin, H.J.P., Bouzembrak, Y., Fels-Klerx, H.J.V.D., Kempenaar, C., Veerkamp, R., Chauhan, A., Stroosnijder, S., Top, J., Simsek-Senel, G., Vrolijk, H., Knibbe, W.J., Zhang, L., Boom, R., Tekinerdogan, B., 2022. Digitalization

- and artificial intelligence for sustainable food systems. *Trends in Food Science & Technology* 120, 344–348.
- McFadden, J., Casalini, F., Griffin, T., Anton, J., 2022. The digitalization of agriculture: a literature review and emerging policy issues. Available at https://www.oecd.org/content/dam/oecd/en/publications/reports/2022/04/the-digitalisation-of-agriculture_dd2a1973/285cc27d-en.pdf (accessed 21 January 2026).
- McGrath, J.E., 1981. Dilemmatics: the study of research choices and dilemmas. *American Behavioral Scientist* 25, 179–210.
- McKinion, J.M., Lemmon, H.E., 1985. Expert systems for agriculture. *Computers and Electronics in Agriculture* 1, 1, 31–40.
- McIntosh, M.J., Morse, M.J., 2015. Situating and constructing diversity in semi-structured interviews. *Global Qualitative Nursing Research* 2, 1–12.
- Mhlanga, D., Ndhlovu, E., 2023. Digital technology adoption in the agriculture sector: challenges and complexities in Africa. *Human Behavior and Emerging Technologies* 2023, 6951879.
- Mishra, D., Muduli, K., Raut, R., Narkhede, B.E., Shee, H., Jana, S.K., 2023. Challenges facing artificial intelligence adoption during COVID-19 pandemic: an investigation into the agriculture and agri-food supply chain in India. *Sustainability* 15, 6377.
- Mohr, S., Kuhl, R., 2021. Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture* 22, 1816–1844.
- Narayanamurthy, G., Jayanth, R.S.S., Tortorella, G., Fogliatto, F., 2025. Empirical investigation of barriers and benefits of smart farming. *International Journal of Quality & Reliability Management* 42, 8, 2150–2173.
- Nitsch, U. 1990. Farmers and computers. In Göranson, B., Florin, M. (eds) *Artificial Intelligence, Culture and Language: On Education and Work*. Springer, London, pp. 115–126.
- Nonaka, I., Takeuchi, H., 1995. *The knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation*. Oxford University Press, New York.
- Nowell, L.S., Norris, J.M., White, D.E., Moules, N.J., 2017. Thematic analysis: striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods* 16, 1–13.
- O’Keefe, J., Buytaert, W., Mijic, A., Brozovic, N., Sinha, R., 2016. The use of semi-structured interviews for the characterization of farmer irrigation practices. *Hydrology and Earth System Sciences* 20, 1911–1924.
- Omotayo, A.O., Adediran, S.A., Omotoso, A.B., Olagunju, K.O., Omotayo, O.P., 2025. Artificial intelligence in agriculture: ethics, impact possibilities, and pathways for policy. *Computers and Electronics in Agriculture* 239, 110927.
- Papadimitriou, F., 2012. Artificial intelligence in modelling the complexity of Mediterranean landscape transformations. *Computers and Electronics in Agriculture* 81, 87–96.
- Partel, V., Costa, L., Ampatzidis, Y., 2021. Smart tree crop sprayer utilizing sensor fusion and artificial intelligence. *Computers and Electronics in Agriculture* 191, 106556.
- People’s Daily Online., 2025. AI-powered robotic dogs ‘take over’ inspections at vegetable production base in Shouguang, E China’s Shandong. Available at [http://en.people.cn/n3/2025/0303/c90000-20283588.html#:~:text=Artificial%20intelligence%20\(AI\)%2Dpowered%20robotic%20dogs%20are%20now%20handling,city%2C%20east%20China%27s%20Shandong%20Province.](http://en.people.cn/n3/2025/0303/c90000-20283588.html#:~:text=Artificial%20intelligence%20(AI)%2Dpowered%20robotic%20dogs%20are%20now%20handling,city%2C%20east%20China%27s%20Shandong%20Province.) (accessed 16 April 2025).
- Ployhart, R.E., Vandenberg, R.J., 2010. Longitudinal research: the theory, design, and analysis of change. *Journal of Management* 36, 1, 94–120.
- Puppala, H., Peddinti, P.R.T., Tamvada, J.P., Ahuja, J., Kim, B., 2023. Barriers to the adoption of new technologies in rural areas: the case of unmanned aerial vehicles for precision agriculture in India. *Technology in Society* 74, 102335.
- Raj, A., Jeyaraj, A., 2023. Antecedents and consequents of industry 4.0 adoption using technology, organization and environment (TOE) framework: a meta-analysis. *Annals of Operations Research* 322, 101–124.
- Rashid, A.B., Kausik, M.D.A.K., 2024. AI revolutionizing industries worldwide: a comprehensive overview of its diverse applications. *Hybrid Advances* 7, 100277.
- Rauch, B., Matar, R., Dorr, I.G., 2025. Unlocking the potential of artificial intelligence for sustainable agriculture. Available at <https://digital-strategy.ec.europa.eu/en/library/unlocking-potential-artificial-intelligence-sustainable-agriculture> (accessed 15 September 2025).

- Rodzi, Z.M., Rosly, N.A.M., Zaik, N.M.A., Rusli, M. H., Ahmad, G., Al-Sharqi, F., Al-Quran, A., Bany Awad, A.M.A., 2024. A DEMATEL analysis of the complex barriers hindering digitalization technology adoption in the Malaysia agriculture sector. *Journal of Intelligent Systems and Internet of Things* 13, 1, 21–30.
- Rogers, E.M., 1995. *Diffusion of Innovations* (4th edn). Free Press, New York.
- Saad, N.H.M., Yaacob, Z., Peng, W.W., Anwar, M.F., 2024. A model of adoption determinants of IoT within the T-O-E framework in the Malaysian agriculture sector. *Global Business and Management Research: An International Journal* 16, 4s, 1886–1898.
- Saha, A., Raut, R., Kumar, M., 2025. Digital technology adoption challenges in the agri-food supply chain from the perspective of attaining sustainable development goals. *The International Journal of Logistics Management* 36, 2, 556–588.
- Saunders, M., Lewis, P., Thornhill, A., 2019. *Research Methods for Business Students* (8th edn). Pearson Education Limited, England.
- Schwartz, S.H., 2006. A theory of cultural value orientations: explication and applications. *Comparative Sociology* 5, 2-3, 137–182.
- Scoutlabs, 2025. *Challenges in AI adoption for agriculture and easy pest management solutions*. Available at <https://scoutlabs.ag/ai-challenges-agriculture-pest-management/> (accessed 10 April 2025).
- Senna, P.P., Ferreira, L.M.D.F., Barros, A.C., Roca, J.B., Magalhaes, V., 2022. Prioritizing barriers for the adoption of Industry 4.0 technologies. *Computers & Industrial Engineering* 171, 108428.
- Shahadat, M.M.H., Nekmahmud, Md., Ebrahimi, P., Fekete-Farkas, M., 2023. Digital technology adoption in SMEs: what technological, environmental and organizational factors influence in emerging countries? *Global Business Review*. <https://doi.org/10.1177/09721509221137199>
- Shankar, P., Werner, N., Selinger, S., Janssen, O., 2020. Artificial intelligence driven crop protection optimization for sustainable agriculture. 2020 IEEE/ITU International Conference on Artificial Intelligence for Good (AI4G), Geneva, Switzerland, pp. 1-16.
- Silveira, F.D., Silva, S.L.C.D., Machado, F.M., Garcia, J., Barbedo, A., Amaral, F.G., 2023a. Farmers' perception of the barriers that hinder the implementation of agriculture 4.0. *Agricultural Systems* 208, 103656.
- Silveira, F.D., Barbedo, J.G.A., Silva, S.L.C.D., Amaral, F.G., 2023b. Proposal for a framework to manage the barriers that hinder the development of agriculture 4.0 in the agricultural production chain. *Computers and Electronics in Agriculture* 214, 108281.
- Smidt, H.J., Jokonya, O., 2022. Factors affecting digital technology adoption by small-scale farmers in agriculture value chains (AVCs) in South Africa. *Information Technology for Development* 28, 3, 558–584.
- Sood, A., Bhardwaj, A.K., Sharma, R.K., 2024. Towards sustainable agriculture: key determinants of adopting artificial intelligence in agriculture. *Journal of Decision Systems* 33, 4, 833–877.
- Srinivasan, K., Yadav, V.K., 2024. An empirical investigation of barriers to the adoption of smart technologies integrated urban agriculture systems. *Journal of Decision Systems* 33, 4, 878–912.
- Sun, W., Bocchini, P., Davison, B.D., 2020. Applications of artificial intelligence for disaster management. *Natural Hazards* 103, 2631–2689.
- Susanty, A., Puspitasari, N.B., Junaidi, S.E., Wicaksono, H., 2025. Mapping barriers to digital adoption in Batik MSMEs: insights from DEMATEL-ISM integration. *International Journal of Information Technology*. <https://doi.org/10.1007/s41870-025-02839-9>
- Sushil, 2012. Interpreting the interpretive structural model. *Global Journal of Flexible Systems Management* 13, 2, 87–106.
- The State Council, 2020. China takes training of high-quality farmers to new level. Available at https://english.www.gov.cn/statecouncil/ministries/202011/26/content_WS5fbf0869c6d0f72576940b21.html (accessed 17 September 2025).
- Thomasson, J.A., Ampatzidis, Y., Bhandari, M., Thomasson, J.A., Ampatzidis, Y., Bhandari, M., Ferreyra, R.A., Gentimis, T., McReynolds, E., Murray, S.C., Peterson, M.B., Rodriguez Lopez, C.M., Strong, R. L., Tedeschi, L.O., Vitale, J., Ye, X., 2025. AI in agriculture: opportunities, challenges, and recommendations. Available at https://cast-science.org/wp-content/uploads/2025/03/CAST_AI-in-Agriculture.pdf (accessed 15 September 2025).
- Tornatzky, L.G., Fleischer, M., 1990. *The processes of technological innovation*. Lexington Books, Lexington.
- Trendov, N.M., Varas, S., Zeng, M., 2019. Digital technologies in agriculture and rural areas–status report. Available at <https://openknowledge.fao.org/server/api/core/bitstreams/0bb5137a-161c-4b7c-9257-3d4d5251b4bf/content> (accessed 21 January 2026).

- Tzachor, A., 2021. Barriers to AI adoption in Indian agriculture: an initial inquiry. *International Journal of Innovation in the Digital Economy* 12, 3.
- Vahdanjoo, M., Sorensen, C.G., Norremark, M., 2025. Digital transformation of the agri-food system. *Current Opinion in Food Science* 63, 101287.
- VandenBos, G.R. (ed.). 2007. *APA Dictionary of Psychology*. American Psychological Association, Washington, DC.
- Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. *MIS Quarterly* 27, 3, 425–478.
- Wang, Y., Jin, L., Mao, H., 2019. Farmer cooperatives' intention to adopt agricultural information technology—mediating effects of attitude. *Information Systems Frontiers* 21, 565–580.
- Warren, C.A., 2002. Qualitative interviewing. In Gubrium, J.G., Holstein, J.A. (eds) *Handbook of Interview Research: Context and Method*. Sage, Thousand Oaks, pp. 83–99.
- Wellman, N., Troster, C., Grimes, M., Roberson, Q., Rink, F., Gruber, M., 2023. From the editors: publishing multithreshold research in AMJ: a review and best-practice recommendations. *Academy of Management Journal* 66, 4, 1007–1015.
- Wolf, E.J., Harrington, K.M., Clark, S.L., Miller, M.W., 2013. Sample size requirements for structural equation models: an evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement* 76, 6, 913–934.
- Yadav, D.K., Barve, A., 2016. Modelling post-disaster challenges of humanitarian supply chains: a TISM approach. *Global Journal of Flexible Systems Management* 17, 3, 321–340.
- Yang, R., Zhang, M., Zhang, Y., 2024. A system dynamics model based on ISM for risk perception in emergency by employees in chemical industrial parks. *Scientific Reports* 14, 25767.
- Yin, W., 2023. Does digital transformation matter to green innovation: based on TOE framework and configuration perspective. *Environmental Science and Pollution Research* 30, 100046–100057.
- Zhang, D., Wang, G., 2024. The sustainability journey of Chinese ready-meal companies going global: configuration analysis using the technology-organizational-environment framework. *Foods* 13, 14, 2251.
- Zhao, G., Liu, S., Lopez, C., Chen, H., Lu, H., Mangla, S.K., Elgueta, S., 2020. Risk analysis of the agri-food supply chain: a multi-method approach. *International Journal of Production Research* 58, 16, 4851–4876.
- Zhao, G., Xie, Y., Dennehy, D., Wamba, S.F., 2025. Understanding supply chain knowledge mobilization barriers from the middle-range perspective: an empirical investigation of Argentina's agri-food industry. *Journal of Business Logistics* 46, 2, e70009.
- Zhao, G., Ye, C., Dennehy, D., Liu, S., Harfouche, A., Olan, F., 2024a. Analysis of barriers to adopting Industry 4.0 to achieve agri-food supply chain sustainability: a group-based fuzzy analytic hierarchy process. *Business Strategy and the Environment* 33, 8, 8559–8586.
- Zhao, G., Liu, S., Lopez, C., Wang, Y., Lu, H., Zhang, J., 2024b. Identification, establishment of connection, and clustering of social risks involved in the agri-food supply chains: a cross-country comparative study. *Annals of Operations Research* 338, 1241–1282.
- Zhao, G., Liu, S., Wang, Y., Lopez, C., Zubairu, N., Chen, X., Xie, X., Zhang, J., 2024c. Modelling enablers for building agri-food supply chain resilience: insights from a comparative analysis of Argentina and France. *Production Planning & Control* 35, 3, 283–307.
- Zhao, Z., Shan, R., Sun, X., Sun, J., Wang, B., Wang, Z., 2023. Mapping and assessing supply and demand of crop pollination services in Shandong province, China. *Journal of Cleaner Production* 426, 139024.

Appendix 1: Interview guide

Section 1 Introductory questions

A. Interviewee background information

1. What is your current role or designation on the farm?
2. Can you briefly describe your key responsibilities within the farm's operations?
3. How long have you been working on this farm?

4. How many years of experience do you have in agriculture or related fields?

B. Farm background information

1. Could you provide an overview of the farm's structure and operations (e.g., locations, departments, number of employees, and main businesses)?

Section 2 Current and planned adoption of AI-enabled digital technologies

1. What AI-enabled digital technologies have been adopted on your farm so far?

2. How are these technologies integrated into your day-to-day operations?

3. In what ways have these technologies impacted your farm's: cost structure? Productivity or efficiency? Market competitiveness or sustainability?

4. Are there any AI or digital technologies you are planning to adopt in the near future? If yes, which ones and why?

Section 3 Challenges to the adoption of AI-enabled digital technologies

A. Technological challenges

1. What technological challenges have you encountered (or foresee) when adopting AI-enabled digital technologies?

2. How do these challenges affect your ability to fully implement or benefit from these technologies?

3. Have you taken any steps to overcome these challenges? If so, what were they and how effective have they been?

B. Organizational challenges

1. Are there challenges related to training, staff acceptance, or organizational readiness?

2. How do you address these human or organizational issues when implementing new technologies?

C. Environmental challenges

1. Are there any external barriers, such as regulations or funding limitations, that impact technology adoption?

2. What recommendations would you make to government bodies or industry stakeholders to tackle environmental challenges?

Appendix 2: Initial reachability matrix

	T1	T2	T3	T4	T5	T6	O1	O2	E1	E2	E3	I1	I2
T1	1	0	1	0	1	1	0	0	0	0	0	0	0
T2	1	1	1	0	0	0	0	0	0	0	0	0	0
T3	0	0	1	0	0	1	0	0	0	0	0	0	1
T4	0	1	0	1	0	0	0	1	0	0	0	0	1
T5	0	0	0	1	1	0	0	0	0	0	0	0	1
T6	0	1	0	0	1	1	0	0	0	0	0	0	0
O1	0	1	0	0	0	1	1	0	0	0	0	0	1
O2	0	0	0	0	0	1	0	1	0	0	0	0	1
E1	0	0	1	0	0	0	0	0	1	0	0	0	0
E2	0	1	1	1	0	1	1	1	0	1	0	1	1
E3	1	1	1	1	1	1	0	0	1	0	1	0	0
I1	0	0	0	0	0	0	1	1	0	0	0	1	1
I2	0	1	0	0	0	0	0	0	0	0	0	0	1

Appendix 3: partitioning the reachability matrix into different levels

Challenge	Reachability set (RS)	Antecedent set (AS)	$RS \cap AS$	Level
Iteration 1				
T1	T1, T2, T3, T4, T5, T6, O2, I2	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	
T2	T1, T2, T3, T4, T5, T6, O2, I2	T1, T2, T4, T5, T6, O1, E2, E3, I1, I2	T1, T2, T4, T5, T6, I2	
T3	T3, T6, I2,	T1, T2, T3, T4, T5, O1, E1, E2, E3, I1	T3	
T4	T1, T2, T3, T4, T5, T6, O2, I2	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	
T5	T1, T2, T3, T4, T5, T6, O2, I2	T1, T2, T4, T5, T6, O1, E2, E3, I1	T1, T2, T4, T5, T6	
T6	T2, T5, T6	T1, T2, T3, T4, T5, T6, O1, O2, E2, E3, I1	T2, T5, T6	I
O1	T1, T2, T3, T4, T5, T6, O1, I2	O1, E2, I1	O1	
O2	T6, O2, I2	T1, T2, T4, T5, O2, E3, I1	O2	
E1	T3, E1, I2	E1, E3	E1	
E2	T1, T2, T3, T4, T5, T6, O1, O2, E2, I1, I2	E2	E2	
E3	T1, T2, T3, T4, T5, T6, O2, E1, E3, I2	E3	E3	
I1	T1, T2, T3, T4, T5, T6, O1, O2, I1, I2	E2, I1	I1	
I2	T2, I2	T1, T2, T3, T4, T5, O1, O2, E1, E2, E3, I1, I2	T2, I2	I

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Challenge	Reachability set (RS)	Antecedent set (AS)	$RS \cap AS$	Level
Iteration 2				
T1	T1, T2, T3, T4, T5, O2	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	
T2	T1, T2, T3, T4, T5, O2	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	
T3	T3	T1, T2, T3, T4, T5, O1, E1, E2, E3, I1	T3	II
T4	T1, T2, T3, T4, T5, O2	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	
T5	T1, T2, T3, T4, T5, O2	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	
O1	T1, T2, T3, T4, T5, O1	O1, E2, I1	O1	
O2	O2	T1, T2, T4, T5, O2, E3, I1	O2	II
E1	T3, E1	E1, E3	E1	
E2	T1, T2, T3, T4, T5, O1, O2, E2, I1	E2	E2	
E3	T1, T2, T3, T4, T5, O2, E1, E3	E3	E3	
I1	T1, T2, T3, T4, T5, O1, O2, I1	E2, I1	I1	
Iteration 3				
T1	T1, T2, T4, T5	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	III
T2	T1, T2, T4, T5	T1, T2, T4, T5, T6, O1, E2, E3, I1	T1, T2, T4, T5	III
T4	T1, T2, T4, T5	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	III
T5	T1, T2, T4, T5	T1, T2, T4, T5, O1, E2, E3, I1	T1, T2, T4, T5	III
O1	T1, T2, T4, T5, O1	O1, E2, I1	O1	
E1	E1	E1, E3	E1	III
E2	T1, T2, T4, T5, O1, E2, I1	E2	E2	
E3	T1, T2, T4, T5, E1, E3	E3	E3	
I1	T1, T2, T4, T5, O1, I1	E2, I1	I1	
Iteration 4				
O1	O1	O1, E2, I1	O1	IV
E2	O1, E2, I1	E2	E2	
E3	E3	E3	E3	IV
I1	O1, I1	E2, I1	I1	
Iteration 5				
E2	E2, I1	E2	E2	
I1	I1	E2, I1	I1	V
Iteration 6				
E2	E2	E2	E2	VI

Appendix 4: Fuzzy direct reachability matrix

	T1	T2	T3	T4	T5	T6	O1	O2	E1	E2	E3	I1	I2
T1	0	0	0.7	0	0.7	0.3	0	0	0	0	0	0	0
T2	0.7	0	0.7	0	0	0	0	0	0	0	0	0	0
T3	0	0	0	0	0	0.3	0	0	0	0	0	0	0.5
T4	0	0.5	0	0	0	0	0	0.7	0	0	0	0	0.5
T5	0	0.3	0	0.7	0	0	0	0	0	0	0	0	0.5
T6	0	0.3	0	0	0.3	0	0	0	0	0	0	0	0
O1	0	0.7	0	0	0	0.5	0	0	0	0	0	0	0.3
O2	0	0	0	0	0	0.7	0	0	0	0	0	0	0.7
E1	0	0	0.7	0	0	0	0	0	0	0	0	0	0
E2	0	0.3	0.1	0.3	0	0.5	0.7	0.7	0	0	0	0.5	0.7
E3	0.7	0.5	0.5	0.7	0.3	0.3	0	0	0.5	0	0	0	0
I1	0	0	0	0	0	0	0.5	0.5	0	0	0	0	0.7
I2	0	0.3	0	0	0	0	0	0	0	0	0	0	0