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## Smart farming uptake: understanding the forces behind adoption in the Western Zone of Tamil Nadu

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### ABSTRACT

**Purpose:** Farming challenges continue to affect labor availability, environmental sustainability and economic viability. Smart Farming Technologies (SFTs) offer a data-driven approach to enhance efficiency and sustainability in agricultural practices. This study examines the key factors influencing farmers' adoption of SFTs, while addressing the current gap in empirical research.

**Design/methodology/approach:** The study analyzed adoption factors using the TOE (Technology-Organization-Environment) framework based on data collected from 150 farmers. Stratified random sampling was used to ensure representation across different categories of farmers (small, medium and large landholders). The research model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM).

**Findings:** The results indicate that technological and organizational factors are critical in determining adoption behavior, whereas environmental factors exert a comparatively moderate influence.

**Practical implications:** The study informs policymakers and Agri-Tech stakeholders on key drivers of smart farming technology adoption. Emphasis should be placed on enhancing organizational readiness and building trust in technology providers. Targeted extension and advisory interventions can support adoption across diverse farming categories.

**Theoretical implications:** This research extends the TOE framework within the agricultural context, confirming the importance of technological and organizational factors. It provides empirical evidence on the comparatively moderate role of environmental factors. The use of PLS-SEM enhances methodological rigor for future empirical research.

**Originality/value:** Using a stratified farmer sample, the study provides empirical evidence on smart farming adoption. It offers insights into the role of trust and organizational dynamics in adoption behavior. The research adds value by grounding theoretical models in real-world agricultural settings.

### ARTICLE HISTORY

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### KEYWORDS

Smart farming; agricultural innovation; farmers; technology adoption; TOE framework; PLS-SEM

## 1. Introduction

Agriculture has remained fundamental to human existence, evolving together with technological advancement. In recent years, the emergence of smart farm technologies such as precision farming, Internet of Things (IoT), Artificial Intelligence (AI) and big data analytics has significantly transformed modern agricultural practices. These technologies offer substantial potential to enhance productivity, sustainability and efficiency through data-driven decision-making. However, despite their potential benefits, the adoption of such technologies varies considerably among farmers, indicating complex and context-specific determinants influencing adoption behavior. Smart farming technologies are increasingly recognized for their role in addressing critical challenges such as water scarcity, resource inefficiency and environmental sustainability. For instance, water-saving technologies and precision irrigation systems contribute to improved water resource management and reduced wastage (Chang et al. 2016; Qazi, Khawaja, and Farooq 2022). These technologies also support sustainable agricultural practices by minimizing input use, reducing operational costs and enhancing productivity (Madushanki et al. 2019; Krishnan et al. 2020; Benyezza, Bouhedda, and Rebouh 2021; Alves, Maia, and Lima 2023). Furthermore, advancements in IoT and digital agriculture have enabled real-time monitoring, automation and improved decision support systems, thereby transforming traditional farming into a more efficient and knowledge-intensive activity (Channe, Kothari, and Kadam 2015; Ibrahim et al. 2018).

The adoption of smart farming technologies is influenced by a multidimensional interplay of economic, social and psychological determinants. Economic determinants, such as investment costs and expected returns play a vital role in determining farmers' intention to invest in new technologies (Caffaro and Cavallo 2019). Technological attributes, including perceived ease of use and compatibility with existing farming practices, further influence the adoption behaviour (Venkatesh et al. 2003). Importantly, social and institutional factors such as extension services, peer networks and government policies play a crucial role in shaping farmers' attitude and decision-making processes (Klerkx, Mierlo, and Leeuwis 2012). These interactions demonstrate that adoption is not purely an economic decision, but is embedded within broader social and institutional contexts. One of the most important drivers of smart farming adoption is the level of education and digital literacy of farmers. Farmers with higher levels of technological literacy and access to digital tools are more likely to adopt smart farming technologies (Rose et al. 2016). Psychological factors such as risk perception and trust in technology providers also influence adoption decisions. Concerns related to data privacy, reliability and fear of change may slow adoption despite favorable economic conditions and infrastructure (Rotz et al. 2019).

To address these challenges, policymakers, technology developers and extension services must develop targeted interventions to accelerate the adoption of smart farming technologies. Targeted training, financial incentives and collaborative networks between farmers and technology providers can significantly enhance adoption rates. Moreover, development of simple, low-cost and context-specific technologies can further promote widespread adoption (Jakku et al. 2019).

In this regard, agricultural extension systems serve as critical intermediaries that facilitate the adoption of innovations by bridging the gap between technology developers and

farmers. Extension services contribute through knowledge dissemination, capacity building, advisory support and strengthening farmer networks, thereby reducing uncertainty associated with new technologies (Klerkx, Mierlo, and Leeuwis 2012; Materia, Giarè, and Klerkx 2015; Landini 2016; Klerkx 2020). With the increasing digitalization of agriculture, extension systems are also evolving to include digital advisory platforms and innovation networks, which play a crucial role in enhancing farmers' awareness and trust in smart farming technologies (Klerkx, Mierlo, and Leeuwis 2012; Klerkx 2020; Klerkx 2021).

Despite the growing body of research on smart farming adoption, limited empirical studies have comprehensively examined the range of factors influencing farmers' adoption behavior, particularly in developing country contexts (Caffaro and Cavallo 2019; Pivoto et al. 2019). Existing research tends to emphasize technological and economic determinants, while comparatively less attention is given to the role of extension systems, social interactions and institutional support (Klerkx, Mierlo, and Leeuwis 2012; Landini 2016). As a result, there remains a limited understanding of how these factors collectively influence farmers' adoption of smart farming technologies.

Addressing this gap, this study uses the Technology-Organization-Environment (TOE) framework (Tornatzky, Eveland, and Fleischer 1990) to examine the factors influencing farmers' adoption of smart farming technologies in the Western zone of Tamil Nadu. The framework has been widely applied in technology adoption studies, including IoT and smart farming contexts (Lin, Lee, and Lin 2016; Pivoto et al. 2019). By incorporating agricultural extension perspectives, the study analyzes how technological, organizational and environmental factors interact with knowledge exchange processes within agricultural innovation systems to shape adoption decisions.

## 2. Conceptual framework

The Technology-Organization-Environment (TOE) framework, originally developed by Tornatzky, Eveland, and Fleischer (1990), provides a theoretical basis for examining the factors influencing technology adoption. It has been extensively applied in studies on technology adoption, including IoT and smart farming contexts (Lin, Lee, and Lin 2016; Madushanki et al. 2019; Pivoto et al. 2019). It explains adoption behaviour through three dimensions: technological, organizational and environmental factors, capturing technology characteristics, farm-level readiness and external conditions.

The Diffusion of Innovation (DOI) theory developed by Rogers (2003) complements the TOE framework by explaining how technological attributes such as relative advantage, compatibility and complexity influence adoption decisions at the individual level.

In addition to these theoretical perspectives, agricultural extension systems play a critical role in shaping farmers' adoption behaviour by facilitating knowledge exchange, capacity building and advisory support. They act as intermediaries by linking farmers with technology providers and institutional support, thereby enabling information flow and social learning (Klerkx, Mierlo, and Leeuwis 2012; Landini 2016; Klerkx 2020).

Accordingly, this study uses the TOE framework, supported by diffusion and extension perspectives, to identify the key factors influencing farmers' adoption of smart farming technologies.

## 2.1. Technological factors

These factors refer to the characteristics of smart farming technologies that influence adoption decisions (Yoon, Lim, and Park 2020).

### 2.1.1. Relative advantage

Relative advantage refers to the extent to which an innovation is perceived as offering greater benefits compared to existing practices (Rogers 2003). Farmers are more likely to adopt smart farming technologies when they perceive improvements in productivity, efficiency and cost savings. Previous studies indicate a positive relationship between perceived benefits and adoption (Henseler, Ringle, and Sinkovics 2009; Yoon, Lim, and Park 2020).

Hypothesis 1: Relative advantage positively influences technology adoption

### 2.1.2. Complexity

Complexity refers to the degree to which smart farming technologies are perceived as difficult to understand and use (Corrocher, Malerba, and Montobbio 2003). Higher perceived complexity may hinder adoption, as it increases the effort required for implementation (Premkumar 2003; Wisdom et al. 2014).

Hypothesis 2: Complexity negatively influences technology adoption

### 2.1.3. Compatibility

The extent to which smart farming technologies align with existing farming practices, values and needs. Compatibility reflects the degree to which an innovation fits with existing practices and needs. Technologies that fit well within existing systems are more likely to be adopted (Bhattacharya and Wamba 2018).

Hypothesis 3: Compatibility positively influences technology adoption.

### 2.1.4. Technology competence

The skills and abilities of farmers to effectively use and manage modern smart farming tools. Such competencies enhance the capacity to utilize technological innovations (Ritter and Gemünden 2004).

Hypothesis 4: Technological competence positively influences technology adoption

### 2.1.5. Cost

Cost refers to the overall financial investment required for the adoption of smart farming technologies including acquisition, installation and maintenance. Costs impede the adoption of innovative technologies. Even when there are potential advantages, the intention to adopt innovations may be diminished if they are perceived to come with undue expenses (Bhattacharya and Wamba 2018).

Hypothesis 5: Costs negatively influences technology adoption.

## **2.2. Organizational factors (farm-level factors)**

These factors relate to the capabilities, readiness and resources of farming enterprises (individual farmers, cooperatives, or FPOs).

### **2.2.1. Technical knowledge**

The level of understanding that farmers have regarding how smart farming technologies function and how to effectively operate and maintain them. Higher levels of knowledge facilitate effective implementation (Kerneck et al. 2020). Extension-led training and advisory support play a key role in enhancing such knowledge (Davis and Sulaiman 2014). Hypothesis 6: Technical knowledge positively influences technology adoption.

### **2.2.2. Farm preparedness**

The extent to which farms are equipped with the necessary infrastructure (electricity, internet connectivity, etc.) to implement and sustain smart farming technologies

Hypothesis 7: Farm preparedness positively influences technology adoption

### **2.2.3. Farm size and resources**

The physical scale of the farm and availability of resources (capital, labor) determine the capacity to invest in and benefit from smart farming technologies.

Hypothesis 8: Farm size and resources positively influence technology adoption

## **2.3. Environmental factors**

These refer to the external conditions that affect the adoption of smart farming technologies.

### **2.3.1. Trust in technology providers**

The level of confidence that farmers have in the reliability and support provided by the technology providers. Extension systems often facilitate trust-building by acting as intermediaries between farmers and service providers.

Hypothesis 9: Trust in Technology providers positively influences technology adoption

### **2.3.2. Competitive pressure**

The influence of neighboring or peer farmers who adopt smart farming practices creates a social or market-driven impetus for change.

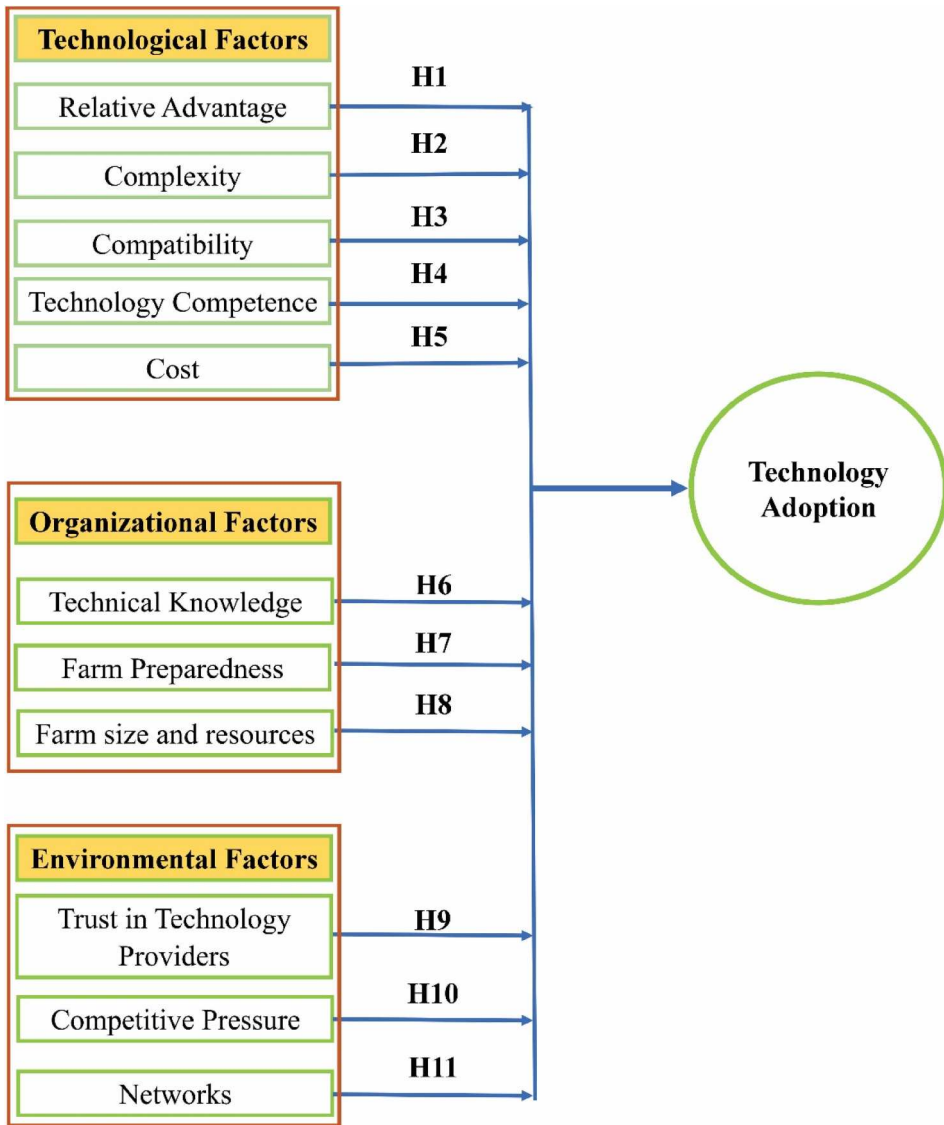
Hypothesis 10: Competitive pressure positively influences technology adoption

### **2.3.2. Networks**

Networks refer to social and institutional linkages that facilitate information sharing and learning among farmers. These networks, often supported by extension systems, influence adoption decisions through knowledge exchange and social learning (Landini 2016; Klerkx 2020).

Hypothesis 11: Networks positively influence technology adoption

The proposed framework integrates the TOE framework with agricultural extension perspectives, providing a comprehensive explanation of smart farming technology adoption within agricultural innovation systems. The conceptual framework of the study is illustrated in [Figure 1](#).



**Figure 1.** Conceptual framework of smart farming technology adoption based on the TOE framework.

### 3. Materials and methods

#### 3.1. Study area

With the second-largest economy in India, Tamil Nadu makes a substantial contribution to the GDP of the country. The state provides a suitable context for investigating the adoption of smart farming technologies due to its growing Agri-Tech ecosystem and innovation potential (NITI Aayog 2020).

Tamil Nadu hosts one of the fastest-growing Agri-tech ecosystems in India, with 137 active Agri-Tech firms spread across its 38 districts, a significant proportion of which are centred in the Western Zone (Startup TN 2020). The Western Zone, which includes

prominent districts such as Erode, Coimbatore and Tiruppur, reflects the varied economic landscape of Tamil Nadu through its vibrant mix of industrial and agricultural activities. The comparatively higher level of technological integration in agriculture within this zone makes it an appropriate setting for examining the adoption dynamics of smart farming practices. Agri-Tech startups are key drivers of innovations related to smart farming. Based on secondary data from Startup TN and ABIS-TBI, TNAU, 12 startups were identified that are actively operating in the study area, covering Coimbatore Erode and Tiruppur districts. These startups provide a range of technologies, including automated irrigation systems, agricultural drone services for spraying fertilizers and herbicides, artificial intelligence-based advisory applications, digital agro-advisory platforms, e-commerce services and automatic weather stations.

### **3.2. Sampling procedure**

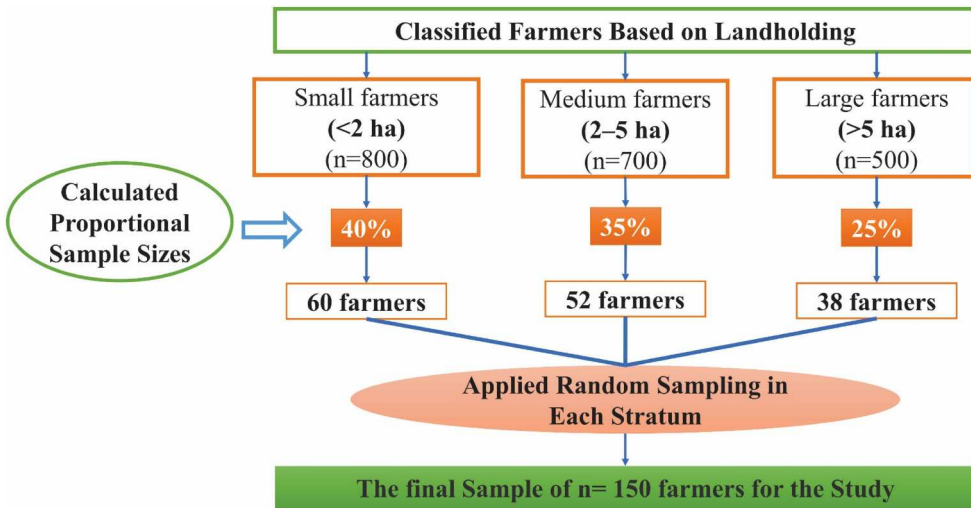
Farmers are the end users of smart farming technologies and their adoption patterns, experiences and intentions are vital to assess the effectiveness and constraints of such technologies. Understanding their attitudes provides significant insights into the determinants influencing the adoption and continued use of these technologies.

The target population (sampling universe) comprised farmers who had adopted smart farming technologies through the identified Agri-Tech startups in the selected districts. The sampling frame was constructed using the customer databases of these startups, which included registered farmers utilizing smart farming technologies. The sampling universe consisted of 2,000 farmers (800 small, 700 medium and 500 large farmers) identified from these databases. Farmers were categorized into three strata based on landholding size following the Government of India classification of operational holdings, namely small (<2 ha), medium (2–5 ha) and large (>5 ha) farmers (Government of India 2016). A stratified random sampling approach was employed, as illustrated in Figure 2, to ensure representation across landholding categories.

The distribution of farmers across the identified startups was uneven; therefore, proportional allocation was applied to ensure representativeness. The proportion of farmers in each landholding category was determined based on their distribution within the sampling frame obtained from the startup databases. This approach ensured that the sample reflected the actual distribution of farmers adopting smart farming technologies. Accordingly, the sampling proportions (40% small-scale, 35% medium-scale, and 25% large-scale farmers) were derived to reflect the actual distribution of adopters. Based on this proportional allocation, a total sample of 150 farmers was selected. Within each stratum, respondents were selected using simple random sampling to minimize selection bias and ensure equal probability of selection.

### **3.3. Construct measures and data collection**

The construct measures were derived from previously validated instruments reported in the literature and were adapted to the context of smart farming technology adoption. The measurement items were carefully modified to ensure contextual relevance while maintaining the conceptual integrity of the original constructs. Items for the relative advantages were adapted from Yoon, Lim, and Park (2020), while the items considering



**Figure 2.** Stratified random sampling procedure based on landholding categories and proportional allocation across strata.

complexity were adapted from Savoury (2019). Items associated with the compatibility construct were adapted from Kernecker et al. (2020). Items related to costs and farm structure factors were derived from Caffaro and Cavallo (2019), Ena and Siewa (2022) and Pandeya, Gyawali, and Upadhaya (2025). The items for trust in technology providers, competitive pressures and networks were adapted from Pivoto et al. (2019), Ena and Siewa (2022) and Jabbari et al. (2023). Content validity was established through expert review, wherein subject matter experts in agricultural extension and smart farming technologies evaluated the relevance and clarity of the measurement items. Based on their feedback, minor modifications were made to improve clarity and contextual appropriateness. A five-point Likert scale ranging from 1 ('strongly disagree') to 5 ('strongly agree') was employed to measure all items.

### 3.4. Data analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyse the relationships between latent constructs and to test the proposed hypotheses (Prasetyo et al. 2020). PLS-SEM is especially suitable for exploratory research, complex models and studies with relatively small sample sizes, as it does not require strict assumptions of data normality (Hair et al. 2019). The analysis was performed in two stages: (i) assessment of the measurement (outer) model and (ii) evaluation of the structural (inner) model. The measurement model was evaluated using reliability and validity indicators, including Cronbach's alpha, Composite Reliability (CR) and Average Variance Extracted (AVE). The structural model was assessed using path coefficients, the coefficient of determination ( $R^2$ ) and predictive relevance ( $Q^2$ ). Bootstrapping, a resampling technique commonly used in PLS-SEM, was applied to evaluate the stability and robustness of model estimates. By generating standard errors and confidence intervals for the path coefficients, it improves the reliability of the results and aids in assessing the model's predictive capability (Stone 1974; Henseler, Ringle, and Sinkovics 2009).

## 4. Results

### 4.1. Outer model assessment

The measurement (outer) model was evaluated to assess construct reliability and validity. Reliability and validity were assessed using Cronbach's alpha, Composite Reliability (CR) and Average Variance Extracted (AVE). As shown in Table 1, all constructs demonstrated acceptable reliability, with Cronbach's alpha values above 0.7, composite reliability above 0.7 (Fornell and Larcker 1981) and AVE above 0.5 (Tabachnick and Fidell 2007), ensuring internal consistency.

Overall, the measurement model assessment indicated strong construct validity and reliability, confirming that the selected variables effectively represent the underlying dimensions influencing technology adoption. The constructs for relative advantage, compatibility, farm preparedness and trust in technology providers showed high internal consistency and reliability. While complexity and cost were identified as barriers, their measurement properties remain reliable. The strong values of Composite Reliability and AVE further validated the robustness of the model, ensuring that the study's findings are theoretically and practically sound. Therefore, the measurement model was considered reliable and valid for subsequent structural model analysis.

### 4.2. Inner model assessment

The structural (inner) model was evaluated to assess the explanatory power and relationships among the constructs. As shown in Table 2, the  $R^2$  value for technology adoption was 0.814, exceeding the threshold of 0.67 and indicating substantial explanatory power (Chin 2001). This indicates that the study's constructs explain 81.4% of the variance in technology adoption.

Predictive relevance of the model was assessed using the Stone-Geisser  $Q^2$  statistic obtained through the blindfolding procedure. The  $Q^2$  value for the endogenous construct (technology adoption) was 0.60, which is greater than zero, indicating strong predictive relevance of the model (Stone 1974; Henseler, Ringle, and Sinkovics 2009).

Following the assessment of the measurement model, the structural relationships were evaluated using standardized path coefficients. The bootstrap method was applied to

**Table 1.** Measurement model assessment (reliability and validity of constructs).

Constructs	Cronbach's $\alpha$	Composite reliability	Average Variance Extracted (AVE)
Relative advantage	0.763	0.859	0.678
Complexity	0.754	0.863	0.671
Compatibility	0.851	0.894	0.628
Technological competency	0.763	0.846	0.585
Cost	0.843	0.894	0.679
Technical knowledge	0.784	0.861	0.608
Farm preparedness	0.824	0.876	0.587
Farm size and resources	0.817	0.879	0.645
Trust in technology providers	0.833	0.878	0.665
Competitive pressures	0.824	0.876	0.585
Networks	0.708	0.835	0.628
Technology Adoption	0.868	0.905	0.657

Source: Results drawn from Smart PLS 4.0 software.

**Table 2.** Coefficient of determination ( $R^2$ ) for the endogenous construct.

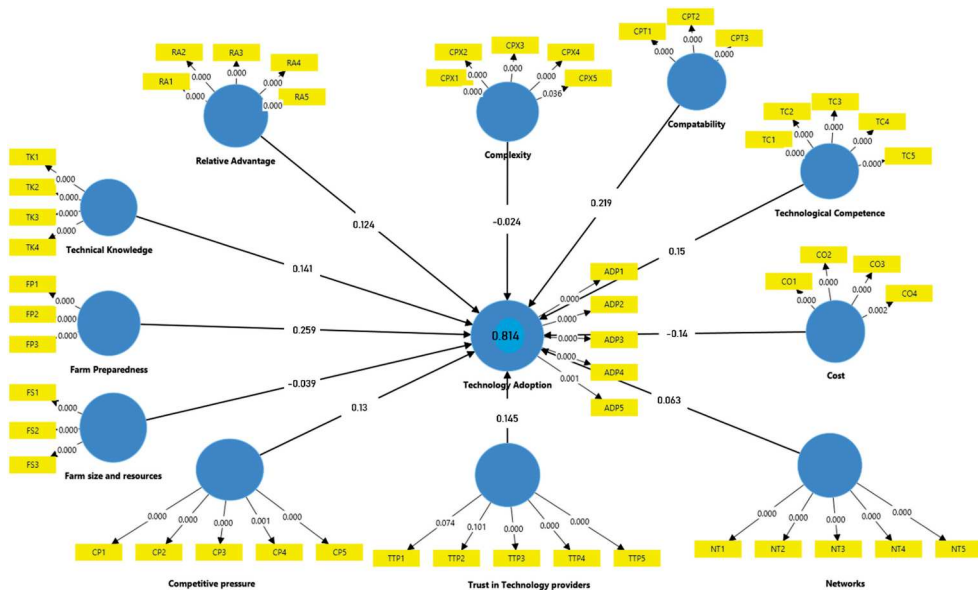
Item	$R^2$	Adjusted $R^2$
Technology adoption	0.814	0.811

**Table 3.** Structural model results (path coefficients and hypothesis testing).

Hypothesis	Path coefficient	t-Value	p-Value	Result
Relative advantage → Technology Adoption	0.124	2.212	0.014	Supported
Complexity → Technology Adoption	-0.024	0.687	0.246	Not Supported
Compatibility → Technology Adoption	0.219	2.793	0.003	Supported
Technological competency → Technology Adoption	0.15	2.368	0.009	Supported
Cost → Technology Adoption	-0.14	2.148	0.016	Supported
Technical knowledge → Technology Adoption	0.141	2.153	0.016	Supported
Farm preparedness → Technology Adoption	0.259	2.178	0.015	Supported
Farm size and resources → Technology Adoption	-0.039	0.967	0.167	Not Supported
Trust in Technology providers → Technology Adoption	0.145	2.654	0.049	Supported
Competitive pressures → Technology Adoption	0.13	3.188	0.037	Supported
Networks → Technology Adoption	0.063	2.354	0.051	Supported

assess the significance of the proposed relationships (Henseler, Ringle, and Sinkovics 2009). To examine the factors driving technology adoption, eleven hypotheses were tested. As presented in Table 3, all hypotheses, except H2 and H8, were supported. The corresponding t-statistics exceeded 1.96, indicating a statistically significant relationship between the constructs and technology adoption.

Figure 3 presented the structural model results, illustrating the relationships among the constructs influencing technology adoption.



**Figure 3.** Structural equation model (SEM) showing relationships among factors influencing smart farming technology adoption.

## 5. Discussion

### 5.1. Technological factors

The results indicate that technological factors play a significant role in shaping farmers' adoption of smart farming technologies. Relative advantage ( $\beta = 0.124, p = 0.014$ ) and compatibility ( $\beta = 0.219, p = 0.003$ ) have a positive and significant influence on adoption, supporting H1 and H3. Technological competency ( $\beta = 0.150, p = 0.009$ ) also shows a significant positive influence (H5 supported), indicating that farmers' ability to operate and manage digital tools further facilitates adoption. These findings suggest that farmers are more likely to adopt smart technologies when they perceive tangible benefits, such as improved input efficiency, reduced labor requirements and enhanced farm management and when these technologies align with existing farming practices. This is consistent with prior studies emphasizing the role of perceived usefulness and compatibility in technology adoption (Oliveira, Thomas, and Espadanal 2014; Gangwar, Date, and Ramaswamy 2015; Arnold and Voigt 2019).

In contrast, cost ( $\beta = -0.14, p = 0.016$ ) exhibits a significant negative effect on adoption (supporting H4), indicating that financial constraints remain a critical barrier. Although complexity ( $\beta = -0.024, p = 0.246$ ) is not statistically significant (H2 not supported), its negative direction suggests that perceived difficulty may still influence adoption decisions, particularly among farmers with limited technical exposure. These findings are consistent with earlier studies highlighting affordability and usability as key determinants in digital agriculture adoption (Lin, Lee, and Lin 2016; Tu 2018) and consistent with agricultural extension research, which emphasizes that advisory services reduce technological uncertainty and facilitate adoption (Landini 2016; Klerkx 2020).

These results indicate that field-level demonstrations and targeted training can address both cost-related perceptions and knowledge gaps. Such interventions improve farmers' understanding of technology benefits and support informed adoption decisions among small and medium farmers.

### 5.2. Organizational factors

Regarding organizational factors, technical knowledge ( $\beta = 0.141, p = 0.016$ ) significantly influences adoption, supporting H6 significantly. This indicates that farmers with higher levels of technical competence are more likely to adopt smart farming technologies. The finding highlights the importance of farm-level human capital in enabling technology adoption, particularly in contexts where digital and data-driven tools require a minimum level of technical understanding. Similar evidence has been reported in studies on digital agriculture adoption, which emphasize that farmers' skills and experiential knowledge are critical determinants of technology uptake (Rose et al. 2016; Kernecker et al. 2020).

Farm preparedness ( $\beta = 0.259, p = 0.015$ ) also shows a significant positive effect (H7 supported), indicating that infrastructure readiness and resource availability facilitate the implementation of smart farming technologies. In contrast, farm size and resources ( $\beta = -0.039, p = 0.167$ ) do not have a significant effect (H8 not supported), suggesting that adoption is not solely determined by farm scale alone but by the capacity to adopt and manage technologies.

Strengthening farmers' competencies through skill-oriented training, on-farm demonstrations and advisory support is essential for enabling effective engagement with smart farming technologies. Prior research similarly highlights that participatory training and advisory systems play a central role in building farmers' capacity to engage with emerging digital innovations (Davis and Sulaiman 2014; Faure, Desjeux, and Gasselin 2012).

### 5.3. Environmental factors

Environmental factors exhibit a moderate but statistically significant influence on adoption. Trust in technology providers ( $\beta = 0.145$ ,  $p = 0.049$ ) and competitive pressure ( $\beta = 0.13$ ,  $p = 0.037$ ) positively influence adoption, supporting H9 and H10, while networks ( $\beta = 0.063$ ,  $p = 0.051$ ) show a marginal effect (H11 supported). These results indicate that adoption decisions are influenced not only by individual and farm-level factors but also by relational and institutional conditions surrounding technology adoption.

Trust in technology providers is particularly important in digitally enabled agriculture, where uncertainty regarding performance, data reliability and service support affects decision-making. This finding is consistent with previous studies indicating that trust and perceived credibility of technology providers significantly influence adoption of precision and digital agricultural technologies (Barnes et al. 2019; Pivoto et al. 2019). Competitive pressure further reinforces adoption, suggesting that peer influence and local innovation environment create incentives for farmers to adopt new technologies.

These results highlight the importance of strengthening interactions among farmers, technology providers and advisory systems. Extension platforms that facilitate farmer-to-farmer exchange, demonstrations and multi-actor engagement can support trust-building and information flow. Previous research shows that network-based learning and multi-stakeholder engagement are critical for enabling innovation uptake within agricultural systems (Leeuwis and Aarts 2011; Ingram and Maye 2020).

This study extends existing research by empirically integrating the TOE framework with agricultural extension perspectives, demonstrating how extension-mediated processes shape smart farming adoption within agricultural innovation systems.

## 6. Conclusion

This study examines the factors influencing farmers' adoption of smart farming technologies, using an integrated Technology-Organization-Environment (TOE) framework. The findings indicate that adoption is influenced by the combination of technological attributes, farm-level capabilities and external conditions. Relative advantage, compatibility, technological competency, technical knowledge and farm preparedness positively influence adoption, while cost remains a significant constraint. Trust in technology providers and competitive pressure also influence farmers' adoption decisions. The results indicate that adoption depends not only on the availability of technologies but also on farmers' capacity to use and integrate them within existing farming systems. This highlights the importance of a system-oriented approach for understanding technology adoption. The study contributes to agricultural extension research by showing how technological, organizational and environmental factors interact within agricultural

knowledge and innovation systems to influence adoption behavior. It further demonstrates that extension-mediated processes, including capacity building and knowledge exchange, play a crucial role in enabling adoption. From a practical perspective, strengthening farmers' technical competencies and facilitating access to advisory services can reduce uncertainty and support effective use of smart farming technologies. These findings provide useful insights for designing extension strategies that support sustainable agricultural digitalization.

### Ethical statement

The study was conducted according to ethical standards. Participation was voluntary, informed consent was obtained from all participants and confidentiality of the data was ensured.

### Disclosure statement

No potential conflict of interest was reported by the author(s).

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