Global Journal of Agrotechnology
Vol. 1 No.1 2026 Page 1-14
E-ISSN: XXXX-XXXX, DOI: 10.XXXXX/XXXX

A Model for the Adoption of IoT-Based Precision Agriculture Technology to Enhance Productivity and Sustainability Among Smallholder Farmers

Niken Hermawan[1]*, Rahmat Safitri[2], Anisa Maharani[3]
[1,2] Department of Agricultural Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia
[3] Department of Agroecotechnology, Faculty of Agriculture, Universitas Brawijaya, Malang, Indonesia

Article Info

Received : 4 February 2026
Revised : 5 April 2026
Accepted : 19 April 2026

Keyword:

Iot-Based Precision Agriculture;
Smallholder Farmers;
Technology Adoption;
Digital Agriculture;
Sustainability;
Grounded Theory.

ABSTRACT

This study aims to formulate a model for the adoption of IoT-based precision agriculture technology to enhance productivity and sustainability among smallholder farmers. The study responds to the limited understanding of how smallholder farmers interpret, evaluate, and adopt digital agricultural technologies within real farming contexts. A qualitative approach with a constructivist grounded theory design was used to explore farmers' experiences and adoption processes. Data were collected from smallholder farmers, agricultural extension officers, farmer group leaders, AgTech actors, and supporting institutions through semi-structured interviews, field observations, documentation, and triangulation. The findings reveal seven main categories influencing IoT adoption: individual readiness, perceived usefulness, perceived ease of use, trust in data, social support, facilitating conditions, and sustainability alignment. Farmers understood IoT less as a technical system and more as a practical tool for reducing uncertainty, improving irrigation and fertilization decisions, managing input costs, and sustaining farm productivity. Trust in digital data emerged through repeated field validation, peer confirmation, and extension support. Farmer groups functioned as social infrastructure that enabled collective learning, technology demonstration, and shared risk reduction. The study contributes to technology adoption literature by integrating technology acceptance theory, diffusion of innovation theory, and agricultural innovation systems. The findings imply that IoT adoption strategies should prioritize affordability, simplicity, maintenance support, rural connectivity, extension capacity, and group-based implementation. Future research should test the proposed model quantitatively across different commodities and regions.

***) Corresponding Author:**

Niken Hermawan,
Department of Agricultural Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia
Email: niken.hermawan091@gmail.com

1. Introduction

Global agriculture is moving toward production systems that rely more on data, connectivity, sensors, and digital decision-making. This shift occurs because agriculture faces complex pressures, including climate change, water scarcity, soil degradation, rising food demand, and the need for more efficient input use. Digital agriculture does not only refer to the use of modern devices. It also changes how farmers, extension officers, markets, and supporting institutions manage production information. Lajoie-O'Malley et al. (2020) argue that the future of digital agriculture is closely linked to the development of sustainable food systems. Bahn et al. (2021) also show that digitalization can support economic, social, and environmental efficiency in agri-food systems. In this context, the Internet of Things (IoT) has become one of the main foundations of precision agriculture because it enables real-time data collection through soil moisture sensors, temperature sensors, weather monitoring tools, irrigation systems, crop sensors, and environmental monitoring devices. Dhanaraju et al. (2022) explain that IoT helps farmers manage resources more accurately. Karunathilake et al. (2023) add that precision agriculture supports more accurate, efficient, and adaptive farming decisions.

IoT-based precision agriculture has strong relevance for smallholder farmers because this group often faces limitations in capital, land size, technological access, digital literacy, internet connectivity, and technical assistance. On the one hand, IoT can help smallholder farmers reduce the inefficient use of water, fertilizer, labor, and pesticides. On the other hand, this technology requires social, economic, and institutional readiness, which is not always available in rural areas. Friha et al. (2021) explain that IoT implementation in smart agriculture requires the integration of sensor devices, communication networks, computing systems, and decision-support systems. Ronaghi and Forouharfar (2020) found that IoT acceptance in smart farming is shaped by performance expectancy, ease of use, social influence, and facilitating conditions. Li et al. (2020) also show that precision agriculture adoption depends not only on technical benefits, but also on farmers' perceptions of risk, technological needs, and user readiness. DeLay et al. (2022) found that precision agriculture can improve technical efficiency when farmers use it as part of consistent farm management. Carrer et al. (2022) also demonstrate that technology adoption produces stronger benefits when farmers integrate it into farm operations rather than use it as a single stand-alone tool.

In Indonesia, the adoption of digital agricultural technology still faces clear challenges among smallholder farmers. Satria et al. (2025) found that smallholder farmers in Indonesia face barriers related to limited digital literacy, uneven internet access, high costs, lack of training, and weak technical support. This condition shows that IoT adoption cannot be understood only as a matter of providing technological devices. It also relates to farmers' ability to read data, trust digital recommendations, understand economic benefits, and adapt technology to established farming habits. Hoang and Tran (2023) show that younger, better educated, better trained, and more extension-connected smallholder farmers tend to show higher readiness to adopt digital technology. Miine et al. (2023) found that the intensity of digital agricultural service use depends on information access, experience, and socioeconomic capacity. Choruma et al. (2024) add that smallholder farmers in developing regions still face barriers related to cost, skills, infrastructure, and the relevance of digital services to local needs. These findings indicate that an IoT adoption model for smallholder farmers must reflect their real social context rather than simply transfer technology models from large-scale commercial farms.

The adoption of IoT in precision agriculture can be explained through technology acceptance theory, diffusion of innovation theory, and the agricultural innovation systems perspective. In the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology, technology acceptance is influenced by perceived usefulness, perceived ease of use, social influence, and facilitating conditions. Giua et al. (2022) show that smart farming technology adoption does not happen through a single simple decision. It develops through gradual processes shaped by intention, farmer characteristics, and farm structure. Thomas et al. (2023) explain that smart agriculture acceptance is influenced by productivity expectations, ease of access to information, training, technology complexity, infrastructure needs, and technology suitability. John et al. (2023) also emphasize that precision agriculture adoption among small-scale farmers is shaped by economic, technological, social, institutional, and environmental factors. Dibbern et al. (2024) found that the main barriers to digital agriculture adoption include economic constraints, infrastructure limitations, technological knowledge gaps, and perceived risk. Osrof et al. (2023) argue that research on smart farming adoption needs to pay closer attention to operational field contexts, not only to users' intention to adopt technology.

Although studies on smart farming, digital agriculture, and precision agriculture continue to grow, important gaps remain in the literature. Many previous studies still focus on technological design, technical efficiency, or quantitative measurement of adoption factors. Getahun et al. (2024) show that precision agriculture technology can support productivity and environmental sustainability, but studies in this area often position technology mainly as a technical instrument. Manzoor et al. (2025) show that digital agriculture technology adoption in low- and middle-income countries is influenced by social, economic, technical, institutional, and policy factors. However, fewer studies have explored how smallholder farmers interpret IoT, how they evaluate digital data, how they build trust in technological recommendations, and how social relations within farmer groups influence adoption decisions. This gap matters because technology adoption is not only an individual rational decision. It is also a social process shaped by experience, habits, trust, extension relationships, group support, capital access, perceived risk, and sustainability values.

Based on this background, this study aims to formulate an adoption model for IoT-based precision agriculture technology that is relevant for smallholder farmers in improving productivity and farm sustainability. The study focuses on smallholder farmers' experiences, perceived technological benefits, adoption barriers, digital literacy readiness, institutional support, trust in data, and the meaning of sustainability in daily farming practices. This study offers a theoretical contribution by expanding the understanding of agricultural technology adoption through the integration of technology acceptance theory, diffusion of innovation theory, and agricultural innovation systems. In practical terms, the findings can guide AgTech developers, extension officers, cooperatives, local governments, and policymakers in designing IoT adoption strategies that are more inclusive, affordable, and suitable for smallholder farming conditions. Therefore, this study positions IoT not only as a technical device, but also as part of an agricultural transformation process that requires human readiness, institutional support, and a strong enabling ecosystem.

2. Materials and Methods

The author(s) must describe exactly the steps: what and how experiments were run, what, how This study uses a qualitative approach with a constructivist grounded theory design. This approach was selected because the study does not only aim to describe the use of IoT-based precision agriculture technology. It also aims to build a conceptual model of technology adoption among smallholder farmers. Constructivist grounded theory enables the researcher to develop categories and relationships between categories based on field data. Charmaz and Thornberg (2021) explain that grounded theory can generate substantive theory that remains close to participants' experiences and social contexts. Lim (2025) also states that qualitative research is suitable for understanding experiences, meanings, social processes, and contextual dynamics that cannot always be explained through numbers. Therefore, this approach is appropriate for exploring how smallholder farmers understand IoT, assess its benefits and risks, and decide whether the technology is useful for their farming activities.

The study was conducted in three agricultural production areas in West Java, namely Subang Regency, Indramayu Regency, and West Bandung Regency. These locations were selected because they represent smallholder farming characteristics, crop diversity, and early exposure to digital agricultural technologies, such as weather information applications, digital consultation services, soil moisture sensors, data-based irrigation systems, and agricultural marketing platforms. Data collection was carried out from March to May 2025. The locations were selected because agricultural regions in Indonesia show different levels of digital readiness, especially in infrastructure, digital literacy, extension access, and financing capacity. Satria et al. (2025) show that AgTech adoption barriers in Indonesia are still related to cost, literacy, infrastructure, and technical support. Therefore, the selected locations allowed the study to capture diverse smallholder experiences in facing the opportunities and barriers of IoT adoption.

Participants were selected using purposive sampling and snowball sampling. Purposive sampling was used to identify informants who had direct experience or relevant knowledge of smallholder farming, digital agriculture, agricultural extension, and precision agriculture technology. The farmer informant criteria included managing or owning less than two hectares of land, actively conducting farming activities, having used or known digital agricultural technology, being connected to a farmer group, and being willing to share information openly. The informants consisted of 20 smallholder farmers, 5 agricultural extension officers, 3 farmer group or cooperative administrators, 2 AgTech actors, and 2 representatives of supporting institutions or local agencies. Snowball sampling was used to identify additional informants recommended by initial participants, especially farmers who had tried sensors, agricultural applications, weather information services, or digital consultation platforms. Recruitment stopped when the data reached saturation, meaning that new interviews no longer produced meaningful new themes.

Data were collected through semi-structured interviews, field observation, documentation, and method triangulation. Semi-structured interviews were used because they allowed the researcher to explore participants' experiences and perceptions in depth while maintaining focus on the research objectives. Adeoye-Olatunde and Olenik (2021) explain that semi-structured interviews allow researchers to use guiding questions and ask follow-up questions based on participants' answers. Each interview lasted around 45 to 75 minutes. Interviews were conducted at farmers' homes, farms, farmer group halls, extension offices, or other agreed locations. The interview questions covered farmers' experiences in making cultivation decisions, understanding of IoT, perceived technological benefits, cost barriers, trust in digital data, extension support, farmer group influence, digital literacy readiness, and the meaning of productivity and sustainability for smallholder farmers.

Field observation was conducted to understand actual farming conditions and the use of technology in farmers' daily practices. The researcher observed land management patterns, crop monitoring practices, water use, fertilizer use, access to weather information, interaction with extension officers, and the use of digital devices in production activities. Documentation was carried out by collecting field photos, extension records, training materials, screenshots of agricultural applications, farmer group records, and local policy documents related to agricultural digitalization. Observation and documentation were needed so that interview data could be compared with evidence from field practice. Dhanaraju et al. (2022) explain that IoT in agriculture can include sensors, communication networks, crop monitoring systems, weather data, and decision-support systems. Friha et al. (2021) also emphasize that IoT implementation in smart agriculture depends on the connectivity of devices, data, and decision-making systems. Therefore, this study did not only explore farmers' perceptions, but also examined how technology appears in actual cultivation practices.

Data trustworthiness was maintained through source triangulation, method triangulation, member checking, and audit trail. Source triangulation was conducted by comparing information from farmers, extension officers, farmer group administrators, AgTech actors, and representatives of supporting institutions. Method triangulation was conducted by comparing interview, observation, and documentation data. Member checking was carried out by confirming interview summaries and initial interpretations with several key participants to ensure that the meaning of the data did not deviate from their experiences. Audit trail was conducted by keeping records of the research process, interview transcripts, analytical memos, code lists, category changes, and methodological decisions. Johnson et al. (2020) emphasize that rigor in qualitative research needs to be shown through design transparency, reflexivity, and analytical traceability. Yadav (2022) also explains that qualitative research quality can be assessed through credibility, coherence, data depth, and alignment between research questions, methods, analysis, and conclusions.

Data analysis was carried out through open coding, axial coding, and selective coding. In the open coding stage, the researcher repeatedly read the transcripts to identify units of meaning related to perceived benefits, cost barriers, technological risk, trust in data, extension support, farmer group influence, digital literacy, and sustainability orientation. In the axial coding stage, these codes were grouped into larger categories, such as individual readiness, social readiness, infrastructure readiness, institutional support, perceived value, perceived risk, and farm sustainability. In the selective coding stage, the researcher connected the core categories to build an adoption model for IoT-based precision agriculture among smallholder farmers. The analysis was conducted iteratively through constant comparison between data, codes, categories, and analytical memos. Braun and Clarke (2021) emphasize that theme-based analysis must be conducted reflectively so that themes do not merely summarize data, but also explain patterns of meaning. Through this procedure, the study is expected to produce an adoption model that is empirical, contextual, and replicable in a limited way in other smallholder farming areas with similar characteristics.

3. Results and Discussions

3.1 Practical Understanding of IoT-Based Precision Agriculture

The findings show that smallholder farmers understood IoT-based precision agriculture through practical farming needs rather than through technical concepts. Most participants did not define IoT as a network of connected sensors, digital devices, cloud systems, or data analytics platforms. They described it as a tool that could help them solve real problems in the field, such as deciding when to irrigate, when to apply fertilizer, how to monitor soil moisture, how to anticipate pest attacks, and how to respond to uncertain rainfall. This practical understanding indicates that farmers evaluated technology based on its usefulness in daily farming activities, not based on its technical sophistication. Farmer 03 stated, “The most important thing is not the name of the technology, but whether it can tell us when the soil is dry and when the crop needs water.” This statement reflects the way smallholder farmers translated IoT into practical value. For them, technology became meaningful when it helped reduce uncertainty, save time, and support better decisions in cultivation.

Several farmers linked IoT to the possibility of reducing uncertainty in farming decisions. They explained that farming practices had long depended on experience, visual observation, seasonal habits, and advice from older farmers. These forms of local knowledge remained important, but farmers also recognized that climate variability, irregular rainfall, rising input prices, and pest outbreaks made traditional decision-making less predictable. Farmer 07 explained, “If the tool can show soil moisture, we do not need to guess every day.” This statement shows that farmers did not see IoT as a replacement for local knowledge. They saw it as additional support that could strengthen their judgment. Observations also showed that farmers who had used weather applications or simple soil moisture devices were more likely to describe IoT as a tool for reading field conditions. Therefore, adoption began when farmers recognized that existing practices were no longer sufficient to manage new production risks.

3.2 Perceived Benefits of IoT Adoption

The second major finding concerns farmers’ perceived benefits of IoT-based precision agriculture. Farmers believed that IoT could improve productivity when it helped them make timely, accurate, and more confident cultivation decisions. They associated the technology with better control over irrigation, fertilizer application, pest monitoring, and crop condition assessment. Productivity was not understood only as higher yield at harvest. It was also understood as the ability to reduce mistakes, prevent delays, and respond more quickly to changing field conditions. Farmers explained that data from sensors, applications, and weather information systems could help them know when crops needed water, when fertilizer should be applied, and when field conditions required closer attention. This finding shows that perceived usefulness emerged from direct links between technology and cultivation decisions. Farmers were more interested in technology when they could see how it worked in the field and how it could improve their farming outcomes.

Farmers also emphasized input efficiency as an important benefit of IoT adoption. Rising prices of fertilizer, pesticides, fuel, labor, and irrigation costs made farmers more sensitive to technologies that could reduce waste. Farmer 11 stated, “Fertilizer is expensive now, so if the application can help us use it at the right time, it is useful.” This statement shows that farmers evaluated IoT through a practical economic calculation. They wanted to know whether the technology could help them reduce unnecessary input use and maintain profit margins. Field observations confirmed that farmers responded more positively to technologies that offered visible cost-saving benefits, especially tools that could reduce repeated field checking, prevent excessive watering, and improve fertilizer timing. In this context, IoT was not only perceived as a modern agricultural tool. It was viewed as a possible strategy for managing production costs and protecting farm income under uncertain economic conditions.

3.3 Barriers to IoT Adoption

Despite recognizing the potential benefits of IoT, farmers identified several barriers that limited adoption. The most frequent barrier was cost. Many farmers perceived sensors, internet packages, subscriptions, device installation, and maintenance as additional financial burdens. Farmer 14 stated, “Even if the tool is useful, we must think about whether the harvest can pay for it.” This statement illustrates that adoption decisions were closely tied to household economic calculations. Farmers did not only ask whether the technology worked. They also asked whether the technology could generate benefits that were greater than the costs. For smallholder farmers, investment in technology competes with other urgent needs, such as seeds, fertilizer, family expenses, labor costs, and debt repayment. Therefore, even when farmers saw IoT as useful, they remained cautious if the cost was too high or if the return on investment was unclear.

Connectivity emerged as another major challenge in IoT adoption. Several farming areas had unstable internet signals, especially in plots located far from village centers or in areas with weak telecommunication infrastructure. This condition limited the use of real-time applications, cloud-based monitoring, digital consultation services, and sensor systems that required continuous data transmission. Farmer 18 explained, “The signal is sometimes lost in the field, so the application cannot always be used when we need it.” This finding shows that infrastructure readiness directly affects farmers’ willingness to use IoT systems. Farmers were reluctant to depend on digital tools when they could not access them consistently in the field. Maintenance also became a major concern because farmers worried about damaged sensors, battery replacement, calibration, spare parts, and repair services. AgTech Actor 01 noted, “Many farmers are interested at first, but they become hesitant when they ask who will repair the device if it breaks.” This shows that technology adoption depends not only on access to devices but also on long-term support.

3.4 Trust in Digital Data

Trust became a central theme in the adoption process. Farmers did not immediately accept digital recommendations, sensor readings, or application advice as fully reliable. They compared digital information with their own experience, direct field observation, bodily knowledge, and advice from other farmers. Farmer 05 stated, “We still look at the soil with our hands. If the data says dry but the soil feels wet, we ask again.” This statement shows that local knowledge remained important in evaluating technological information. Farmers did not reject digital data, but they tested it through familiar ways of knowing. Trust emerged gradually when sensor readings matched field conditions and when digital recommendations produced visible benefits. Therefore, trust in IoT was not automatic. It was built through repeated use, comparison, confirmation, and evidence from actual farming practice.

Trust was also shaped by social confirmation and extension support. Farmers were more willing to try IoT when other farmers in the same group had already used it and reported positive results. Farmer 09 stated, "If a neighbor has tried it and the result is good, we become more confident." This finding indicates that adoption spread through social learning and peer validation. Extension officers also played a key role in translating digital data into practical cultivation decisions. Farmers often needed assistance to interpret sensor readings, understand application recommendations, and decide what actions should follow after receiving data. Extension Officer 04 explained, "The data alone is not enough because farmers need to know what action should be taken after reading the data." This finding indicates that IoT adoption requires human mediation. Digital data becomes useful only when farmers can connect it with concrete farming actions.

3.5 Farmer Groups as Social Infrastructure for IoT Adoption

The findings show that farmer groups played a crucial role in introducing, testing, and legitimizing IoT-based precision agriculture. Farmer groups provided spaces for collective learning, discussion, demonstration, and evaluation. Farmers were more willing to engage with IoT when the technology was introduced through trusted group leaders, extension officers, cooperatives, or local networks. Farmer Group Leader 01 stated, "Farmers rarely decide alone when the tool is new. They usually ask the group first." This statement shows that adoption decisions were embedded in collective social relations. The group helped reduce uncertainty by allowing farmers to share experiences, compare results, ask questions, and negotiate possible costs. In some cases, farmer groups also became potential entry points for shared ownership of sensors or irrigation monitoring tools.

Observation data showed that farmers responded more positively during demonstration sessions than during formal presentations. When farmers saw sensor readings, application dashboards, or irrigation recommendations in the field, they asked more specific questions about cost, durability, maintenance, expected benefits, and compatibility with their crops. This suggests that adoption is more likely when technology is introduced through participatory and practice-based learning. Demonstration helped farmers connect abstract technological concepts with concrete farming problems. It also allowed them to evaluate whether the technology was suitable for their land, crop type, financial capacity, and daily routines. Therefore, farmer groups were not only social organizations. They also functioned as learning spaces that could make digital agriculture more accessible and understandable for smallholder farmers.

3.6 Sustainability Meaning Among Smallholder Farmers

Farmers did not always describe sustainability in formal environmental terms. They often understood sustainability as the ability to continue farming despite rising costs, climate uncertainty, water scarcity, and declining soil quality. Farmer 12 stated, "Sustainable farming means we can still plant next season and not lose money." This statement indicates that sustainability was closely linked to economic survival. For smallholder farmers, a sustainable farming system must help maintain income, reduce production risk, and support continuity across planting seasons. This finding shows that sustainability cannot be separated from livelihood security. Farmers became interested in IoT when they believed that the technology could support farm continuity by reducing waste, improving timing, preventing crop stress, and helping them manage limited resources more carefully.

At the same time, farmers recognized that efficient use of water, fertilizer, and pesticides was important for long-term farming. Farmer 16 explained, "If we use too much chemical input, the soil becomes tired." This statement shows that farmers had ecological awareness, although it was often expressed through practical farming language rather than formal sustainability concepts. Farmers understood soil fatigue, water waste, and excessive chemical use as problems that could threaten future production. IoT was seen as useful when it helped farmers reduce waste and protect land productivity. The findings suggest that the sustainability value of IoT must be communicated through farmers' everyday concerns. Abstract messages about environmental sustainability may not be enough. Farmers responded more strongly to clear links between technology, lower input costs, better crop condition, water savings, and continued farming viability.

3.7 Emerging Model of IoT Adoption Among Smallholder Farmers

Based on the data analysis, the adoption of IoT-based precision agriculture among smallholder farmers can be understood through seven interrelated categories: individual readiness, perceived usefulness, perceived ease of use, trust in data, social support, facilitating conditions, and sustainability alignment. Individual readiness includes digital literacy, openness to learning, age, farming experience, and willingness to try new practices. Perceived usefulness refers to farmers' belief that IoT can improve productivity, reduce input waste, and support better decisions. Perceived ease of use relates to whether farmers can operate the technology without excessive technical difficulty. Trust in data refers to farmers' confidence in sensor readings, application recommendations, and digital advice. Social support includes farmer groups, extension officers, peer farmers, cooperatives, and AgTech providers. Facilitating conditions include internet access, device affordability, training, maintenance, and financing. Sustainability alignment refers to whether IoT supports farmers' goals related to income stability, resource efficiency, and long-term land productivity.

These categories form a process-based model of adoption. Farmers first recognized production problems, such as unstable rainfall, high input prices, pest pressure, water scarcity, and uncertainty in cultivation decisions. They then evaluated whether IoT offered practical value for solving those problems. After that, they sought confirmation from direct experience, peer farmers, farmer groups, extension officers, and technology providers. Adoption became more likely when the technology was affordable, understandable, reliable, supported, and aligned with farming needs. However, adoption remained partial or temporary when cost, connectivity, maintenance, trust, or institutional support remained weak. This model shows that IoT adoption among smallholder farmers is not a single decision. It is a gradual, social, and context-dependent process that moves from awareness to trial, validation, trust formation, and continued use.

Discussion

The results show that IoT adoption among smallholder farmers is not a purely technical process. It is a social, economic, and institutional process shaped by farmers' daily experiences, production risks, financial capacity, and trust relationships. This finding supports technology acceptance theory, especially the idea that perceived usefulness and perceived ease of use influence technology adoption. Farmers in this study showed interest in IoT when they believed that the technology could help them reduce uncertainty, improve productivity, save input costs, and make better cultivation decisions. This aligns with Ronaghi and Forouharfar (2020), who found that performance expectancy and facilitating conditions shape IoT acceptance in smart farming. However, the findings also show that technology acceptance among smallholder farmers cannot be explained only through individual perception. It must also be understood through social support, institutional readiness, and local farming realities.

The finding on farmers' practical understanding of IoT confirms that smallholder farmers adopt technology based on problem-solving value. Farmers did not need complex technical explanations about sensor architecture, cloud platforms, or data systems before they became interested in IoT. They needed evidence that IoT could help them decide when to irrigate, when to fertilize, how to monitor soil conditions, how to respond to pests, and how to reduce input waste. This finding is consistent with Thomas et al. (2023), who explain that smart agriculture acceptance depends on productivity expectations, training, infrastructure, and technology suitability. It also supports Karunathilake et al. (2023), who emphasize that precision agriculture contributes to more accurate and adaptive farm management. Therefore, IoT solutions for smallholder farmers should begin with local production problems rather than with technological promotion.

This study also shows that technology acceptance theory needs contextual extension when applied to smallholder farmers. Farmers did not evaluate IoT only through individual perceptions of usefulness and ease of use. They also relied on social confirmation, extension support, farmer group discussions, and direct demonstration. This finding supports diffusion of innovation theory, which views adoption as a process influenced by communication channels, peer networks, and social systems. It also supports John et al. (2023), who found that precision agriculture adoption among small-scale farmers is shaped by economic, technological, social, institutional, and environmental factors. In this study, adoption decisions were socially embedded because farmers often waited for evidence from trusted peers before making their own decisions. This means that technology acceptance should be understood as both an individual and collective process.

Social validation played a major role in shaping farmers' willingness to adopt IoT. Farmers became more confident when other farmers had already tried the technology and reported positive results. This finding shows that peer experience can reduce perceived risk and increase perceived usefulness. Farmer groups, informal conversations, demonstration plots, and extension meetings became channels through which farmers evaluated technology collectively. This pattern strengthens the argument that innovation does not spread only through information transfer. It spreads through trust, observation, comparison, and shared experience. Therefore, programs that aim to introduce IoT-based precision agriculture should involve farmer champions, group-based demonstrations, and peer learning mechanisms. These strategies can help farmers move from curiosity to trial and from trial to sustained use.

The results confirm previous studies on adoption barriers in digital agriculture. Cost, connectivity, digital literacy, and maintenance emerged as major constraints that limited farmers' willingness to adopt IoT. These findings are consistent with Satria et al. (2025), who found that smallholder farmers in Indonesia face barriers related to cost, digital literacy, infrastructure, and technical assistance. They also align with Choruma et al. (2024), who show that smallholder farmers in developing regions face difficulties related to affordability, skills, infrastructure, and technology relevance. In this study, farmers' adoption decisions were strongly influenced by the question of whether the technology could pay for itself through better yields or lower production costs. This indicates that affordability and economic feasibility must become central considerations in IoT design and dissemination.

Farmers' concern about maintenance adds an important practical insight to the literature. Farmers were not only worried about buying technology. They were also worried about repairing and sustaining it after adoption. They asked who would repair damaged sensors, where spare parts could be obtained, how often calibration was needed, and whether the device could survive field conditions. These concerns show that adoption sustainability depends on post-adoption support. If maintenance systems are unclear, farmers may stop using the technology even after initial adoption. Therefore, technology providers, local governments, cooperatives, and extension institutions need to develop reliable service systems. IoT adoption strategies should include repair services, technical assistance, user training, and affordable maintenance packages so that farmers do not feel abandoned after purchasing or receiving the device.

The role of trust in data offers a critical contribution to the literature. Farmers did not reject digital data, but they did not accept it automatically. They tested sensor readings, application recommendations, and extension advice against field experience, bodily knowledge, and social advice. This finding shows that trust is built through interaction between digital evidence and local knowledge. It supports Dibbern et al. (2024), who identify perceived risk and knowledge limitations as major barriers to digital agriculture adoption. In this study, trust was not only cognitive. It was relational and experiential. Farmers trusted technology when the data made sense in the field, when recommendations produced visible results, and when trusted actors could explain the meaning of the data in simple language. This means that trust formation should become a core part of IoT adoption models.

Digital data needed human mediation before it could become useful for farmers. Sensor readings and application recommendations did not automatically lead to action because farmers still needed to understand what the data meant and how they should respond. Extension officers played an important role in translating data into practical decisions, such as when to irrigate, how much water to use, when to apply fertilizer, and when to monitor pests more carefully. This finding shows that digital agriculture should not reduce the importance of extension services. Instead, IoT increases the need for extension officers who can interpret data, explain recommendations, and connect digital information with local farming practices. Therefore, strengthening human capacity is as important as providing technological devices.

Farmer groups emerged as social infrastructure for technology adoption. This finding offers a useful perspective for agricultural innovation systems. IoT adoption cannot rely only on individual farmers or private AgTech providers. It requires networks that connect farmers, extension officers, cooperatives, local governments, and technology developers. Farmer groups helped farmers reduce uncertainty, share costs, test devices, and validate benefits. This finding is consistent with Miine et al. (2023), who show that digital agricultural service adoption depends on access to information and socioeconomic capacity. It also strengthens Hoang and Tran's (2023) finding that extension connection and training increase farmers' readiness to adopt digital technologies. In this study, farmer groups acted as bridges between new technology and local farming routines.

Group-based adoption can make IoT more inclusive for smallholder farmers. Since individual ownership of IoT devices may be too expensive for many farmers, farmer groups and cooperatives can support shared ownership, collective financing, and joint maintenance. This approach can reduce individual risk and increase access for farmers with limited capital. Group-based adoption also supports collective learning because farmers can observe, discuss, and evaluate the technology together. This is important because smallholder farmers often make decisions through social networks rather than through individual calculations alone. Therefore, farmer groups should not be treated only as administrative units. They should be positioned as strategic institutions for technology introduction, experimentation, and long-term adoption support.

The findings show that sustainability has a specific meaning for smallholder farmers. Farmers linked sustainability to economic survival, input efficiency, and the ability to continue farming across planting seasons. This does not mean that farmers ignored environmental concerns. Rather, environmental concerns were expressed through practical issues, such as water savings, soil condition, and reduced chemical use. This finding aligns with Lajoie-O'Malley et al. (2020), who argue that digital agriculture must be understood within broader sustainable food system transitions. It also supports Getahun et al. (2024), who show that precision agriculture can contribute to sustainable crop production and environmental efficiency. The present study adds that sustainability becomes meaningful for smallholder farmers when it is connected to income stability, lower input costs, and long-term land productivity.

The findings suggest that sustainability communication must be grounded in farmers' everyday realities. Abstract messages about environmental protection may not be enough to encourage technology adoption. Farmers responded more strongly to clear links between technology, lower input costs, better crop condition, water savings, soil protection, and continued farming viability. This means that IoT-based precision agriculture should be introduced as a tool that supports both economic resilience and environmental care. For smallholder farmers, sustainability is not only about preserving natural resources. It is also about ensuring that farming remains possible, profitable, and manageable under uncertain conditions. Therefore, adoption strategies should frame IoT as a practical solution for improving productivity, reducing waste, and protecting future farming capacity.

This study offers a new perspective by proposing that IoT adoption among smallholder farmers depends on the interaction of seven categories: individual readiness, perceived usefulness, perceived ease of use, trust in data, social support, facilitating conditions, and sustainability alignment. This model expands existing adoption frameworks by placing trust, social learning, and sustainability alignment at the center of the adoption process. The theoretical implication of this study lies in its integration of technology acceptance theory, diffusion of innovation theory, and agricultural innovation systems. Technology acceptance theory explains why perceived benefits and ease of use matter. Diffusion of innovation theory explains why peer influence and social networks matter. Agricultural innovation systems explain why institutional support, extension services, financing, and technology providers matter. By combining these perspectives, this study shows that IoT adoption is not a single decision. It is a staged process that moves from awareness, interpretation, trial, social validation, trust formation, and continued use.

The practical implications are also important. First, IoT technology for smallholder farmers must be affordable, simple, durable, and supported by clear maintenance services. Second, technology providers should design tools based on farmers' practical problems, not only on technical capacity. Third, extension officers need training so they can help farmers interpret data and translate it into cultivation decisions. Fourth, farmer groups and cooperatives should become entry points for demonstration, shared ownership, and collective financing. Fifth, local governments need to strengthen internet access, digital literacy programs, and rural AgTech support systems. These steps can reduce the gap between technology availability and actual adoption. More importantly, these implications show that successful IoT adoption requires an ecosystem approach that combines technology, financing, training, institutional support, and local trust.

Future research can deepen this study in several ways. Quantitative studies can test the proposed adoption model with a larger sample of smallholder farmers across different regions and commodities. Comparative studies can examine whether the model applies differently to rice, horticulture, plantation crops, and mixed farming systems. Longitudinal studies can also explore how farmers' trust and continued use of IoT change after one or more planting seasons. In addition, future research can examine the economic feasibility of shared IoT ownership through farmer groups, cooperatives, or village-owned enterprises. Such studies would help clarify how IoT-based precision agriculture can become more inclusive, sustainable, and relevant for smallholder farming systems. This future research agenda is important because digital agriculture will only benefit smallholder farmers if adoption models are tested, refined, and adapted to different local contexts.

4. Conclusions

This study concludes that the adoption of IoT-based precision agriculture among smallholder farmers is shaped by the interaction of technical, social, economic, and institutional factors. Farmers did not understand IoT mainly as a complex digital system, but as a practical tool that could help them reduce uncertainty, improve cultivation decisions, increase input efficiency, and support farming continuity. The findings show that adoption depends on seven key categories: individual readiness, perceived usefulness, perceived ease of use, trust in data, social support, facilitating conditions, and sustainability alignment. Trust emerged as a central factor because farmers evaluated digital data through field experience, local knowledge, peer confirmation, and extension support. Farmer groups also played an important role as social infrastructure that enabled collective learning, technology demonstration, and shared decision-making.

Theoretically, this study contributes to the literature by extending technology acceptance theory through the integration of diffusion of innovation theory and agricultural innovation systems. The study shows that IoT adoption among smallholder farmers is not a single individual decision, but a staged process involving awareness, practical evaluation, trial, social validation, trust formation, and continued use. Practically, the findings suggest that IoT adoption strategies must prioritize affordable devices, simple interfaces, reliable maintenance, field-based training, and strong extension support. From a policy perspective, rural internet access, digital literacy programs, cooperative-based financing, and farmer group-centered innovation programs are needed to make precision agriculture more inclusive. Future research can test the proposed model quantitatively across different regions, crop types, and farming systems to strengthen its generalizability.

References

Adeoye-Olatunde, O. A., & Olenik, N. L. (2021). Research and scholarly methods: Semi-structured interviews. *Journal of the American College of Clinical Pharmacy, 4*(10), 1358–1367. https://doi.org/10.1002/jac5.1441

Bahn, R. A., Yehya, A. A. K., & Zurayk, R. (2021). Digitalization for sustainable agri-food systems: Potential, status, and risks for the MENA region. *Sustainability, 13*(6), 3223. https://doi.org/10.3390/su13063223

Braun, V., & Clarke, V. (2021). Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counselling and Psychotherapy Research, 21*(1), 37–47. https://doi.org/10.1002/capr.12360

Carrer, M. J., Filho, H. M. de S., Vinholis, M. de M. B., & Mozambani, C. I. (2022). Precision agriculture adoption and technical efficiency: An analysis of sugarcane farms in Brazil. *Technological Forecasting and Social Change, 177*, 121510. https://doi.org/10.1016/j.techfore.2022.121510

Charmaz, K., & Thornberg, R. (2021). The pursuit of quality in grounded theory. *Qualitative Research in Psychology, 18*(3), 305–327. https://doi.org/10.1080/14780887.2020.1780357

Choruma, D. J., Dirwai, T. L., Mutenje, M. J., Mustafa, M., Chimonyo, V. G. P., Jacobs-Mata, I., & Mabhaudhi, T. (2024). Digitalisation in agriculture: A scoping review of technologies in practice, challenges, and opportunities for smallholder farmers in Sub-Saharan Africa. *Journal of Agriculture and Food Research, 18*, 101286. https://doi.org/10.1016/j.jafr.2024.101286

DeLay, N. D., Thompson, N. M., & Mintert, J. R. (2022). Precision agriculture technology adoption and technical efficiency. *Journal of Agricultural Economics, 73*(1), 195–219. https://doi.org/10.1111/1477-9552.12440

Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., & Kaliaperumal, R. (2022). Smart farming: Internet of Things (IoT)-based sustainable agriculture. *Agriculture, 12*(10), 1745. https://doi.org/10.3390/agriculture12101745

Dibbern, T., Romani, L. A. S., & Massruhá, S. M. F. S. (2024). Main drivers and barriers to the adoption of digital agriculture technologies. *Smart Agricultural Technology, 8*, 100459. https://doi.org/10.1016/j.atech.2024.100459

Friha, O., Ferrag, M. A., Shu, L., Maglaras, L., & Wang, X. (2021). Internet of Things for the future of smart agriculture: A comprehensive survey of emerging technologies. *IEEE/CAA Journal of Automatica Sinica, 8*(4), 718–752. https://doi.org/10.1109/JAS.2021.1003925

Getahun, S., Kefale, H., & Gelaye, Y. (2024). Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review. *The Scientific World Journal, 2024*, 2126734. https://doi.org/10.1155/2024/2126734

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. https://doi.org/10.1016/j.techsoc.2022.101869

Hoang, H. G., & Tran, H. D. (2023). Smallholder farmers' perception and adoption of digital agricultural technologies: An empirical evidence from Vietnam. *Outlook on Agriculture, 52*(4), 457–468. https://doi.org/10.1177/00307270231197825

John, D., Hussin, N., Shahibi, M. S., Ahmad, M., Hashim, H., & Ametefe, D. S. (2023). A systematic review on the factors governing precision agriculture adoption among small-scale farmers. *Outlook on Agriculture, 52*(4), 469–485. https://doi.org/10.1177/00307270231205640

Johnson, J. L., Adkins, D., & Chauvin, S. (2020). A review of the quality indicators of rigor in qualitative research. *American Journal of Pharmaceutical Education, 84*(1), 7120. https://doi.org/10.5688/ajpe7120

Karunathilake, E. M. B. M., Le, A. T., Heo, S., Chung, Y. S., & Mansoor, S. (2023). The path to smart farming: Innovations and opportunities in precision agriculture. *Agriculture, 13*(8), 1593. https://doi.org/10.3390/agriculture13081593

Lajoie-O'Malley, A., Bronson, K., van der Burg, S., & Klerkx, L. (2020). The future(s) of digital agriculture and sustainable food systems: An analysis of high-level policy documents. *Ecosystem Services, 45*, 101183. https://doi.org/10.1016/j.ecoser.2020.101183

Li, W., Clark, B., Taylor, J. A., Kendall, H., Jones, G., Li, Z., Jin, S., Zhao, C., Yang, G., Shuai, C., Cheng, X., Chen, J., Yang, H., & Frewer, L. J. (2020). A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems. *Computers and Electronics in Agriculture, 172*, 105305. https://doi.org/10.1016/j.compag.2020.105305

Lim, W. M. (2025). What is qualitative research? An overview and guidelines. *Australasian Marketing Journal, 33*(2), 199–229. https://doi.org/10.1177/14413582241264619

MacPherson, J., Voglhuber-Slavinsky, A., Olbrisch, M., Schöbel, P., Dönitz, E., Mouratiadou, I., & Helming, K. (2022). Future agricultural systems and the role of digitalization for achieving sustainability goals: A review. *Agronomy for Sustainable Development, 42*, 70. https://doi.org/10.1007/s13593-022-00792-6

Manzoor, F., Wei, L., Siraj, M., Lu, X., & Qiyang, G. (2025). Digital agriculture technology adoption in low- and middle-income countries: A review of contemporary literature. *Frontiers in Sustainable Food Systems, 9*, 1621851. https://doi.org/10.3389/fsufs.2025.1621851

Miine, L. K., Akorsu, A. D., Boampong, O., & Bukari, S. (2023). Drivers and intensity of adoption of digital agricultural services by smallholder farmers in Ghana. *Heliyon, 9*(12), e23023. https://doi.org/10.1016/j.heliyon.2023.e23023

Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2022). IoT, big data, and artificial intelligence in agriculture and food industry. *IEEE Internet of Things Journal, 9*(9), 6305–6324. https://doi.org/10.1109/JIOT.2020.2998584

Osrof, H. Y., Tan, C. L., Angappa, G., Yeo, S. F., & Tan, K. H. (2023). Adoption of smart farming technologies in field operations: A systematic review and future research agenda. *Technology in Society, 75*, 102400. https://doi.org/10.1016/j.techsoc.2023.102400

Qazi, S., Khawaja, B. A., & Farooq, Q. U. (2022). IoT-equipped and AI-enabled next generation smart agriculture: A critical review, current challenges and future trends. *IEEE Access, 10*, 21219–21235. https://doi.org/10.1109/ACCESS.2022.3152544

Ronaghi, M. H., & Forouharfar, A. (2020). A contextualized study of the usage of the Internet of Things (IoTs) in smart farming in a typical Middle Eastern country within the context of Unified Theory of Acceptance and Use of Technology model (UTAUT). *Technology in Society, 63*, 101415. https://doi.org/10.1016/j.techsoc.2020.101415

Satria, D., Maghraby, W., & Setyanti, A. M. (2025). Digital agricultural technology for smallholder farmers: Barriers and opportunities in Indonesia. *SOCA: Jurnal Sosial Ekonomi Pertanian, 18*(3), 267–281. https://doi.org/10.24843/SOCA.2024.v18.i03.p01

Thomas, R. J., O'Hare, G., & Coyle, D. (2023). Understanding technology acceptance in smart agriculture: A systematic review of empirical research in crop production. *Technological Forecasting and Social Change, 189*, 122374. https://doi.org/10.1016/j.techfore.2023.122374

Yadav, D. (2022). Criteria for good qualitative research: A comprehensive review. *The Asia-Pacific Education Researcher, 31*(6), 679–689. https://doi.org/10.1007/s40299-021-00619-0