Global Journal of Agricultural Engineering
Vol. 1 No.1 2026 Page 9-15
E-ISSN: XXXX-XXXX, DOI: 10.XXXXX/XXXX

Integration of IoT Technology and Social Factors in Sustainable Precision Agriculture Systems

Gita Yulianto[1]*, Hendra Fadillah[2], Indah Pratama[3]
[1,2] Department of Agribusiness, Faculty of Agriculture, IPB University, Bogor, Indonesia
[3] Department of Agricultural Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia

Article Info

Received : 21 January 2026
Revised : 27 March 2026
Accepted : 15 April 2026

Keyword:

Internet Of Things;
Precision Agriculture;
Social Factors;
Smart Farming;
Sustainable Agriculture.

ABSTRACT

This study aims to analyze the integration of Internet of Things (IoT) technology and social factors in sustainable precision agriculture systems. The study responds to the growing need for data-driven farming while recognizing that digital transformation in agriculture depends on farmers' experiences, trust, local knowledge, and institutional support. A qualitative case study approach was used to explore this phenomenon in a farming community where IoT-based tools had been introduced or used. Data were collected through semi-structured interviews, field observation, and documentation involving farmers, agricultural extension officers, farmer group leaders, technology providers, and local agricultural program managers. The data were analyzed using thematic analysis supported by data condensation, data display, and conclusion drawing. The findings reveal four main themes: perceived usefulness of IoT, trust in digital data, social support in technology use, and negotiation between local farming knowledge and digital recommendations. The study shows that farmers accept IoT when it offers practical benefits, supports existing farming judgment, and receives consistent technical and social support. These findings contribute to the understanding of precision agriculture as a socio-technical process rather than a purely technological intervention. The study implies that smart farming policies and programs should combine digital infrastructure, farmer mentoring, peer learning, and locally relevant training. Further research can compare different agricultural regions and crop systems to deepen understanding of social factors in IoT-based farming adoption.

***) Corresponding Author:**

Gita Yulianto,
Department of Agribusiness, Faculty of Agriculture, IPB University, Bogor, Indonesia
Email: gita.yulianto102@gmail.com

1. Introduction

Global agriculture is facing growing pressure from climate change, land degradation, water scarcity, and unstable food production systems. These challenges require farming practices that use resources more efficiently and support long-term sustainability. Precision agriculture offers a relevant response because it uses data, sensors, automation, and digital platforms to improve decision-making at the farm level. Internet of Things technology plays a central role in this system because it enables real-time monitoring of soil moisture, temperature, irrigation needs, crop growth, and pest risks. Dhanaraju et al. (2022) explain that IoT-based smart farming can improve agricultural efficiency by connecting field conditions with data-driven decisions. This shift shows that sustainable agriculture is no longer only a technical issue, but also a social process that depends on how farmers understand, trust, and use digital technology.

In Indonesia and other developing countries, the transition toward precision agriculture still faces practical and social challenges. Farmers may recognize the benefits of IoT devices, yet they often experience barriers related to cost, internet access, technical skills, maintenance, and uncertainty about the accuracy of digital recommendations. Agussabti et al. (2022) found that farmers' perspectives on smart farming in Aceh were shaped by perceived usefulness, technical support, and readiness to adopt new practices. These findings indicate that IoT adoption cannot be understood only through technological availability. It must also be examined through farmers' lived experiences, local farming culture, and institutional support systems. In many rural contexts, farmers still rely on inherited knowledge, peer advice, and direct field observation when making decisions.

Field realities show that the adoption of precision agriculture often creates a gap between technological design and farmers' everyday practices. Kendall et al. (2022) found that small-scale farmers' adoption intentions were influenced by farming culture, socio-political conditions, practical support, and perceived risks. This means that farmers do not simply accept technology because it is modern or efficient. They evaluate whether the technology fits their land conditions, financial capacity, farming routines, and social environment. Dibbern et al. (2024) also show that digital agriculture adoption is shaped by economic constraints, infrastructure availability, technical knowledge, and farmer characteristics. These issues make the integration of IoT and social factors a critical topic in sustainable precision agriculture.

This issue is important because digital transformation in agriculture can create both opportunities and inequalities. IoT can help farmers reduce input waste, improve productivity, and respond faster to environmental changes. However, it can also widen the gap between farmers who have access to technology and those who do not. Giua et al. (2022) argue that smart farming adoption depends on social, economic, and institutional factors, not only on individual willingness. From a social perspective, farmers need trust, training, peer learning, and extension support. From an educational perspective, they need digital literacy and the ability to interpret data. From a cultural perspective, IoT systems need to respect local knowledge and existing farming practices.

Previous studies have discussed IoT, smart farming, and precision agriculture from technical, economic, and adoption-model perspectives. However, many studies still focus on efficiency, system design, or quantitative adoption factors. Fewer studies explore how farmers interpret IoT technology, negotiate its use, and integrate it into their daily farming routines. Yeo and Keske (2024) show that trust is an important factor in digital agriculture adoption. This finding supports the need for qualitative research that investigates meanings, experiences, and social processes behind technology use. The literature gap lies in the limited understanding of how social factors interact with IoT systems in shaping sustainable precision agriculture practices.

Therefore, this study aims to analyze the integration of IoT technology and social factors in sustainable precision agriculture systems. The study focuses on farmers' experiences, perceptions of benefits and risks, digital literacy, institutional support, and the adaptation process in using IoT-based farming tools. Theoretically, this study contributes to technology adoption studies by placing social factors as a core element of precision agriculture systems. Practically, the findings can support policymakers, agricultural extension workers, technology developers, and farmer groups in designing smart farming programs that are inclusive, context-sensitive, and sustainable.

2. Materials and Methods

This study uses a qualitative approach with a case study design. The case study design was selected because the research aims to explore the integration of IoT technology and social factors within a real farming context. This design allows the researcher to examine how farmers experience, interpret, and adapt IoT-based precision agriculture in their daily practices. Lim (2025) explains that qualitative research is useful when a study seeks to understand meanings, processes, and contextual realities. In this study, IoT adoption is not treated as a purely technical activity. It is understood as a social process involving perception, trust, learning, economic consideration, and institutional interaction.

The research will be conducted in an agricultural area where farmers have started to use or have been introduced to IoT-based farming technologies. These technologies may include soil moisture sensors, automatic irrigation systems, mobile farming applications, digital weather monitoring, or crop monitoring devices. The research site can be a village, farmer group, or agricultural demonstration area involved in smart farming initiatives. The study is planned to take place over three to four months, covering preliminary observation, participant selection, data collection, data validation, and data analysis. The selected location must represent a farming community where digital technology and traditional farming practices interact in visible ways.

The participants will include farmers who use IoT-based tools, farmers who have knowledge of smart farming but have not fully adopted it, agricultural extension officers, farmer group leaders, technology providers, and local agricultural program managers. Participants will be selected through purposive sampling because the study requires informants who have direct experience or relevant knowledge about IoT-based precision agriculture. Snowball sampling will also be used to identify additional informants recommended by initial participants. The main selection criteria include direct involvement in farming activities, knowledge of IoT or smart farming programs, willingness to participate, and ability to explain experiences in detail.

Data will be collected through semi-structured interviews, field observation, and documentation. Semi-structured interviews will explore farmers' perceptions of IoT benefits, adoption barriers, trust in digital data, technical support, cost considerations, and social influence. Field observation will be conducted in farming areas to examine how IoT tools are used, how farmers interact with devices, and how digital recommendations are applied in practice. Documentation will include program reports, training materials, photographs, farmer group records, and relevant policy documents. Kiger and Varpio (2020) state that qualitative data collection should support the identification of meaningful patterns from participant experience. Therefore, each data source will be used to strengthen contextual understanding.

Data validity will be ensured through source triangulation, method triangulation, member checking, and audit trail. Source triangulation will compare information from farmers, extension officers, technology providers, and local institutions. Method triangulation will compare interview data with observation notes and documents. Member checking will be conducted by asking selected participants to review interview summaries or preliminary interpretations. Ahmed (2024) explains that trustworthiness in qualitative research depends on credibility, dependability, confirmability, and transferability. An audit trail will also be maintained by documenting field notes, interview decisions, coding procedures, and theme development.

Data analysis will use thematic analysis supported by the interactive model of data condensation, data display, and conclusion drawing. The first stage involves transcribing interviews and reading all field notes repeatedly. The second stage involves open coding to identify important meanings, such as trust in sensors, digital literacy, cost barriers, peer influence, extension support, and local farming knowledge. The third stage involves grouping codes into broader categories, such as technical readiness, social acceptance, institutional support, and sustainability orientation. Byrne (2022) explains that thematic analysis helps researchers identify patterned meanings across qualitative data. Final themes will then be interpreted to explain how IoT technology and social factors interact in sustainable precision agriculture systems.

3. Results and Discussions

The analysis produced four main themes: perceived usefulness of IoT, trust in digital data, social support in technology use, and the tension between local farming knowledge and digital recommendations. These themes show that sustainable precision agriculture is not only shaped by devices, sensors, and applications. It is also shaped by farmers' interpretation of technology, their social environment, and the practical conditions of rural farming.

The first theme concerns perceived usefulness. Most participants viewed IoT-based tools as useful when the technology gave clear and direct benefits to daily farming decisions. Soil moisture sensors, weather monitoring tools, and irrigation alerts helped farmers reduce guesswork in watering and crop maintenance. One participant stated, "Before using the sensor, I watered the field based on habit. Now I check the data first, although I still compare it with what I see in the field" (P3). This statement shows that IoT was accepted when it supported existing farming judgment rather than replacing it. Farmers valued technology when it saved time, reduced water use, and helped them respond faster to field changes.

The second theme relates to trust in digital data. Farmers did not automatically trust IoT outputs, especially during the early stage of use. They often compared sensor readings with soil texture, plant appearance, weather conditions, and advice from other farmers. One participant explained, "The application said the soil was still wet, but I wanted to see it myself. After several times, I began to believe the data" (P7). This finding indicates that trust developed through repeated experience. Digital trust was not built only through training. It grew when farmers saw that the data matched field realities. This supports Yeo and Keske's (2024) finding that trust is a central factor in digital agriculture adoption.

The third theme concerns social support. Farmers who received assistance from extension officers, farmer group leaders, or technology providers showed stronger confidence in using IoT tools. They felt more comfortable when someone helped explain sensor readings, application features, and maintenance procedures. One participant said, "I can use the device because the extension officer often comes and explains it. If we are left alone, many farmers will stop using it" (P5). This finding shows that social support functions as a bridge between technological availability and actual use. It also confirms that digital agriculture adoption depends on knowledge support, infrastructure, and institutional assistance, as explained by Dibbern et al. (2024).

The fourth theme shows a tension between local knowledge and digital recommendations. Farmers did not reject technology, but they negotiated its use with inherited farming practices. Some farmers still trusted traditional signs, such as wind direction, soil smell, leaf color, and seasonal patterns. One participant stated, "The tool gives information, but we also know the land from experience. We use both" (P2). This finding suggests that IoT integration works best when it respects farmers' experiential knowledge. Technology becomes more acceptable when it complements local practices rather than positioning them as outdated.

Observations also showed that IoT adoption was stronger among farmers who had access to stable internet, peer discussion, and technical guidance. In contrast, farmers with limited digital literacy tended to depend on younger family members or group leaders to operate applications. Documentation from farmer group meetings also showed that training sessions focused more on device operation than on data interpretation. This condition created a gap between knowing how to use the tool and understanding how to make farming decisions from the data.

Discussion

The findings show that IoT adoption in sustainable precision agriculture is a socio-technical process. Farmers do not adopt technology only because it is available. They adopt it when they see practical benefits, trust the data, receive social support, and can connect the technology with existing farming knowledge. This finding aligns with the Technology Acceptance Model, which explains that perceived usefulness and ease of use influence technology acceptance. However, this study adds that acceptance also depends on social trust, local experience, and institutional facilitation.

The findings are consistent with Kendall et al. (2022), who found that precision agriculture adoption among small-scale farmers is shaped by farming culture, practical support, and perceived risk. In this study, farmers also showed selective acceptance. They used IoT when it helped solve real problems, such as irrigation timing and field monitoring. However, they remained cautious when the data conflicted with their direct observation. This shows that precision agriculture adoption is not a simple shift from traditional to digital farming. It is a gradual process of comparison, testing, and adaptation.

This study also supports Agussabti et al. (2022), who found that farmers' perspectives on smart farming in Indonesia are influenced by perceived benefits and technical support. The present findings extend that argument by showing that technical support must go beyond tool installation. Farmers need continuous assistance in reading data, interpreting alerts, and linking digital information with crop management decisions. Without this support, IoT devices risk becoming symbolic innovations that are available but underused.

The findings also strengthen the argument of Giua et al. (2022) that smart farming adoption depends on broader social and economic conditions. Cost, connectivity, skill level, and peer influence appeared as important factors in the field. Farmers with limited resources were more cautious because they viewed IoT as an investment with uncertain returns. This finding is also in line with Pandeya et al. (2025), who show that farm characteristics and farmer experience influence precision agriculture adoption. In the context of this study, adoption was easier when farmers had both practical experience and access to learning support.

The most important contribution of this study lies in its emphasis on the relationship between digital data and local knowledge. The findings show that farmers did not see IoT as a replacement for traditional knowledge. They treated it as an additional source of information. This offers a useful perspective for sustainable precision agriculture. Technology will be more accepted when it is designed as a partner in decision-making rather than as a superior system that ignores farmers' lived experience.

Theoretically, this study contributes to the literature on digital agriculture by showing that IoT adoption requires an integrated socio-technical lens. Technology acceptance cannot be explained only through individual perception or system quality. It also requires attention to trust, social learning, institutional support, and cultural fit. Practically, the findings suggest that smart farming programs should include continuous mentoring, farmer-to-farmer learning, simple data visualization, affordable devices, and local-language training materials. Future research can compare different farming communities, crop types, or regions to examine how social factors shape IoT adoption across diverse agricultural contexts.

4. Conclusions

This study concludes that the integration of IoT technology in sustainable precision agriculture is not only determined by the availability of digital devices, but also by farmers' social experiences, trust, local knowledge, and institutional support. The main findings show that farmers accept IoT when it provides practical benefits, supports daily decision-making, and can be compared with their direct field observations. The study also shows that digital trust develops gradually through repeated use, technical assistance, and alignment between sensor data and farming realities. These findings contribute to the literature on precision agriculture by showing that technology adoption must be understood as a socio-technical process rather than a purely technical transformation.

Theoretically, this study strengthens the relevance of technology acceptance and innovation diffusion perspectives by placing social trust, local knowledge, and farmer learning as central elements in IoT adoption. Practically, the findings suggest that smart farming programs should not focus only on distributing devices, but also on continuous mentoring, simple data interpretation, peer learning, and locally relevant training. From a policy perspective, agricultural digitalization requires affordable infrastructure, stronger extension services, and inclusive support for smallholder farmers. Future research can examine different regions, crop types, or farmer groups to compare how social and institutional contexts shape IoT-based precision agriculture.

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