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Strategies for Increasing the Adoption of Precision Agriculture Technologies Among Smallholder Farmers Based on Local Context

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ABSTRACT

This study aims to explore strategies for increasing the adoption of precision agriculture technologies among smallholder farmers based on local context. The issue examined in this study concerns the gap between the potential benefits of precision agriculture and the limited adoption of these technologies among smallholder farmers due to financial, technical, social, and infrastructural constraints. This research used a qualitative case study approach in selected smallholder farming areas in West Java, Indonesia. Data were collected through semi-structured interviews, limited participatory observation, and documentation involving smallholder farmers, farmer group leaders, agricultural extension officers, cooperative managers, local agricultural officials, and technology providers selected through purposive and snowball sampling. The data were analyzed using thematic analysis with stages of data condensation, data display, and conclusion drawing. The findings reveal seven main themes: perceived practical usefulness, affordability and economic risk, trust and peer influence, the role of extension officers, digital literacy and infrastructure, integration between technology and local farming knowledge, and locally suitable adoption strategies. The study shows that adoption increases when technology provides visible benefits, uses simple interfaces, receives institutional support, and enters existing farmer group networks. This study contributes to technology adoption theory by highlighting the role of local context, collective trust, and embodied farming knowledge. The findings imply that policy and practice should prioritize field demonstrations, shared access models, digital extension support, and farmer-centered training.

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1. Introduction

Precision agriculture has become an important strategy for improving agricultural productivity, input efficiency, and environmental sustainability. It uses technologies such as soil sensors, weather-based applications, drones, GPS mapping, satellite imagery, variable-rate input systems, and Internet of Things devices to support more accurate farm decisions. These technologies help farmers manage water, fertilizer, pesticides, labor, and climate risks based on actual field conditions. Onyango et al. (2021) show that precision agriculture can improve resource use efficiency in smallholder farming systems when the technology fits local production conditions.

John et al. (2023) also argue that adoption among small-scale farmers depends on economic, social, technological, and environmental factors that shape farmers' willingness to use new tools.

Smallholder farmers face different adoption problems compared with large commercial farmers. They often manage limited land, depend on family labor, use informal knowledge systems, and make investment decisions under financial uncertainty. Gabriel and Gandorfer (2023) explain that digital technology adoption in small-scale farming often develops gradually, starting from technologies that reduce daily workload and are easy to integrate into existing farm routines. Kendall et al. (2022) found that small-scale family farmers assess precision agriculture through local farming culture, available support, perceived risk, and practical relevance. This indicates that adoption is not only a technical decision. It is also a social process shaped by trust, experience, cost, infrastructure, and local knowledge.

In developing agricultural contexts, the gap between technological promise and field-level adoption remains clear. Many farmers understand that digital tools can improve productivity, but they still hesitate to use them because of high investment costs, limited digital skills, weak internet access, and lack of continuous technical assistance. Miine et al. (2023) found that access to credit, farmer organization membership, and agronomic training increased the adoption of digital agricultural services among smallholder farmers in Ghana. Larasati et al. (2024) showed that farmer readiness to adopt IoT-based monitoring applications in West Java depends on performance expectancy, facilitating conditions, personal innovativeness, and existing habits of farm record keeping. These findings suggest that local capacity matters as much as technological availability.

Empirical studies also show that farmers adopt technology more easily when they can observe its benefits in real farm situations. McCarthy et al. (2023) found that smallholder farmers in Malawi understood the value of drone technology more clearly when they interacted with visual data about field conditions. Jabbari et al. (2023) found that awareness, perceived benefits, training, access to information, and government support influenced farmers' willingness to use IoT-based crop monitoring technologies. Adewopo et al. (2025) further emphasize that digital innovation for smallholder farmers requires user engagement, incentives, and communication strategies that match farmers' daily practices. These studies show that technology adoption strategies need more than training sessions. They need locally trusted learning spaces, demonstration plots, peer learning, and practical proof of economic value.

Several studies have explained the adoption of precision agriculture through the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and diffusion of innovation theory. These theories help explain how perceived usefulness, perceived ease of use, social influence, facilitating conditions, compatibility, observability, and trialability affect adoption decisions. Bagheri et al. (2024) show that perceived usefulness and perceived ease of use influence agricultural extension experts' intentions to use precision agriculture technologies. Cozzi et al. (2025) found that perceived usefulness, social norms, and sustainability benefits influenced farmers' intention to adopt digital technologies in the horticultural sector. However, quantitative models often cannot fully explain how farmers interpret technology through lived experience, local constraints, shared norms, and embodied farming knowledge.

The research gap lies in the limited qualitative understanding of how local context shapes strategies for increasing precision agriculture adoption among smallholder farmers. Prior studies have identified barriers such as cost, infrastructure, training, and digital literacy, but fewer studies explain how farmers negotiate these barriers in everyday farming practice. Van der Velden et al. (2023) show that farmers combine data-driven tools with embodied knowledge and ecological experience when interpreting precision agriculture. Khaspuria et al. (2024) also stress that adoption requires education, infrastructure, policy incentives, and collaboration among stakeholders. Therefore, this study aims to explore strategies for increasing the adoption of precision agriculture technologies among smallholder farmers based on local context. The study focuses on farmers’ perceptions, adoption barriers, support systems, social influence, and locally suitable intervention strategies. The findings are expected to contribute to technology adoption theory and provide practical guidance for extension officers, farmer groups, cooperatives, technology providers, and local governments.

2. Materials and Methods

This study uses a qualitative approach with a case study design. This design fits the research objective because the study seeks to understand how smallholder farmers interpret, accept, resist, and adapt precision agriculture technologies within their local context. A case study allows the researcher to examine adoption as a process that involves social interaction, technical readiness, economic capacity, institutional support, and farmers’ lived experience. Kendall et al. (2022) used a qualitative approach to examine precision agriculture adoption among small-scale family farms and showed that farmer perceptions are shaped by farming culture, practical support, and local agricultural challenges. This study follows that logic by treating adoption as a contextual phenomenon rather than a simple decision to use or reject technology.

The study will be conducted in selected smallholder farming areas in West Java, Indonesia. The proposed sites include Bandung Regency, Garut Regency, and Subang Regency because these areas represent different agricultural characteristics, including horticulture, food crops, and farmer group-based production systems. The research will take place from April to June 2026. These locations are selected purposively because they contain farmers who have been exposed to digital or precision agriculture tools, such as soil moisture sensors, drone services, weather applications, digital farm monitoring, automatic irrigation systems, or mobile-based extension platforms. The West Java context also supports the focus of the study because Larasati et al. (2024) have shown that farmers in this region have begun to engage with IoT-based monitoring applications, although their readiness depends on internal and external conditions.

The participants will include smallholder farmers, farmer group leaders, agricultural extension officers, cooperative managers, local agricultural officials, and agricultural technology providers. The study will use purposive sampling to select informants who have direct knowledge or experience related to precision agriculture adoption. Farmer informants must meet several criteria. They must actively manage a small-scale farm, belong to or interact with a farmer group, have heard about or used at least one precision agriculture technology, and agree to participate voluntarily. Farmer group leaders will be selected because they understand collective decision-making and peer influence. Extension officers will be selected because they know the training process, adoption barriers, and farmer support needs. Snowball sampling will be used after initial interviews to identify other relevant informants, especially farmers who have adopted, rejected, or discontinued specific technologies.

Data will be collected through semi-structured interviews, limited participatory observation, and documentation. Semi-structured interviews will explore farmers’ understanding of precision agriculture, perceived benefits, perceived risks, cost concerns, ease of use, trust in technology, access to training, role of extension officers, farmer group influence, and preferred adoption strategies. Observation will be conducted during farm activities, farmer group meetings, technology demonstrations, or extension sessions. The researcher will observe how farmers discuss technology, how they use or avoid digital tools, and how local actors explain technology benefits. Documentation will include training materials, farmer group records, extension notes, policy documents, photos of activities, and technology-related program documents. This combination supports data richness because adoption can be understood through speech, practice, documents, and social interaction.

The interview guide will be developed based on key concepts from the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and diffusion of innovation theory. The main interview themes will include perceived usefulness, perceived ease of use, compatibility with current farming practices, observability of benefits, trialability, facilitating conditions, social influence, and perceived economic risk. Cozzi et al. (2025) show that perceived usefulness and social norms influence digital technology adoption among farmers. Peña-Holguín et al. (2025) also show that practical functionality, training, and cost affect IoT adoption in agriculture. These concepts will guide the interview structure, but the researcher will allow new themes to emerge from the field so that local meanings and unexpected adoption strategies can be captured.

Data validity will be maintained through source triangulation, method triangulation, member checking, and audit trail. Source triangulation will compare information from farmers, farmer group leaders, extension officers, cooperative managers, local officials, and technology providers. Method triangulation will compare interview findings with observation notes and documents. Member checking will be conducted by asking key informants to review the summary of their interview results and confirm whether the researcher's interpretation reflects their experience. Audit trail will be maintained by organizing interview transcripts, field notes, coding memos, document records, and analytic decisions. This process will strengthen credibility, dependability, and confirmability. Adewopo et al. (2025) emphasize that digital innovation in smallholder systems needs user engagement and contextual communication, so informant confirmation becomes important in this study.

Data analysis will use thematic analysis supported by the interactive model of Miles, Huberman, and Saldaña. The analysis will involve data condensation, data display, and conclusion drawing. First, the researcher will transcribe interviews and read all field notes repeatedly. Second, the researcher will conduct initial coding by marking important statements related to benefits, barriers, trust, costs, infrastructure, training, peer influence, institutional support, and local adaptation. Third, the researcher will group similar codes into broader themes, such as economic barriers, digital literacy constraints, local support systems, demonstration-based learning, collective adoption, and service-based technology access. Fourth, the researcher will compare the themes with prior studies. For example, Miine et al. (2023) found that farmer organizations and credit access support adoption, while McCarthy et al. (2023) showed that visual proof from drone data can strengthen farmer understanding. This comparison will help position the findings within current academic debates.

Ethical procedures will be applied throughout the study. Each participant will receive information about the research purpose, interview process, voluntary participation, and confidentiality. The researcher will request informed consent before collecting data. Participant names, farmer group names, and sensitive local information will be anonymized when needed. The study will not evaluate farmers' technical performance or rank them as successful or unsuccessful adopters. Instead, it will examine how they make sense of precision agriculture technologies within their actual constraints. This design allows limited replication because it provides clear information about location selection, participant criteria, sampling technique, data collection methods, validation procedures, and analysis steps. The expected output is a locally grounded strategy for increasing adoption, including farmer-centered training, demonstration plots, cooperative-based tool sharing, affordable service models, digital extension support, and stronger collaboration among government, extension workers, farmer groups, and technology providers.

3. Results and Discussions

The findings show that smallholder farmers viewed precision agriculture technologies as useful when the technologies produced visible, practical, and immediate benefits for their daily farming activities. Farmers did not reject technology as a concept. They questioned whether the technology could solve real problems such as water scarcity, pest attacks, high fertilizer prices, uncertain weather, and labor shortages. Most participants associated precision agriculture with tools that could help them "see" farm conditions more clearly, especially through weather applications, soil moisture sensors, drone images, and digital advisory platforms. One farmer stated, “I will use the tool if it helps me know when to water and when to apply fertilizer. If it only gives numbers that I do not understand, it is difficult for me.” This statement shows that perceived usefulness was not understood only as technological sophistication. Farmers defined usefulness through simple, direct, and locally meaningful outcomes.

The second theme concerns economic risk and affordability. Participants repeatedly explained that cost remained the strongest barrier to adoption. Farmers understood that precision agriculture could reduce waste and improve productivity, but they hesitated to buy devices individually because farm income was seasonal and uncertain. Several farmers preferred rental services, shared ownership, or cooperative-based access rather than individual purchase. A farmer group leader explained, “If every farmer must buy the tool, only a few will try it. But if the group owns it or rents it together, more farmers will be willing to learn.” This finding indicates that adoption strategies should not rely only on individual ownership. For smallholder farmers, shared access models may reduce financial risk and increase experimentation.

The third theme relates to trust, peer influence, and demonstration-based learning. Farmers were more willing to adopt technology after seeing other farmers use it successfully. Interviews showed that formal explanations from technology providers were less persuasive than direct proof from neighboring farmers or farmer group demonstrations. One participant said, “When the officer explains, we listen. But when we see the result in another farmer’s field, we start to believe.” Observations during farmer group meetings also showed that farmers asked more questions when they saw photos, field maps, or yield comparisons from local demonstration plots. This pattern suggests that adoption is strongly shaped by social learning, local evidence, and trust networks.

The fourth theme shows the strategic role of agricultural extension officers and farmer group leaders. Extension officers were seen as important translators between technology providers and farmers. Farmers expected them to simplify technical language, explain the economic benefits, and assist during early use. However, some participants also reported that extension officers did not always have enough technical capacity to explain new digital tools. One farmer stated, “Sometimes the extension officer also learns together with us. If there is no technician, we are afraid the tool will not be used again.” This finding highlights the need to strengthen extension capacity, especially in digital literacy, troubleshooting, and farmer-centered communication.

The fifth theme concerns digital literacy and infrastructure limitations. Farmers who owned smartphones were more familiar with weather applications, online marketplaces, and agricultural information platforms. However, they still faced difficulties in interpreting sensor data, using digital dashboards, and connecting devices to unstable internet networks. Older farmers often depended on younger family members or farmer group administrators to operate mobile applications. One older participant explained, “I can use WhatsApp, but for applications with many menus, I ask my son to help.” This shows that digital literacy is not only an individual skill issue. It also involves household support, intergenerational learning, and the design of user-friendly technology.

The sixth theme reveals that farmers did not want technology to replace their local farming knowledge. They wanted technology to support experience-based decisions. Farmers still relied on soil texture, leaf color, rainfall patterns, pest signs, and inherited planting calendars. Precision agriculture was accepted when it confirmed or improved this local knowledge. It was resisted when it seemed to ignore farmers’ experience. One farmer stated, “The tool can help, but we still know our land. Sometimes the land condition is different from what the application says.” This finding shows that adoption requires integration between data-based recommendations and embodied farming knowledge. Farmers need space to compare technology outputs with their own field experience.

The seventh theme concerns locally suitable adoption strategies. Participants suggested several strategies: practical training in the field, demonstration plots, group-based tool sharing, affordable service packages, continuous technical assistance, local language manuals, and involvement of farmer group leaders. Farmers also preferred technologies that addressed urgent problems, such as water management, pest detection, fertilizer efficiency, and weather prediction. Based on interviews and observations, adoption was more likely when technology was introduced gradually, linked to existing farmer group routines, and supported by actors trusted by the community. The findings indicate that increasing adoption requires more than technology distribution. It requires a social system that helps farmers test, understand, trust, and adapt technology to local farming conditions.

Discussion

The findings support the Technology Acceptance Model, especially the importance of perceived usefulness and perceived ease of use in shaping technology adoption. Farmers in this study were willing to use precision agriculture technologies when they saw clear benefits for irrigation, fertilizer use, pest control, labor efficiency, and production risk reduction. This aligns with Bagheri et al. (2024), who found that perceived usefulness and ease of use influenced agricultural extension experts' intention to use precision agriculture technologies. It also supports Jabbari et al. (2023), who showed that farmers' awareness, training, perceived benefits, and government support influenced IoT adoption in crop monitoring. However, this study adds that usefulness must be translated into locally understood benefits. Farmers did not evaluate usefulness through abstract productivity claims. They assessed it through visible results in their own fields or in nearby farms.

The findings also extend the Unified Theory of Acceptance and Use of Technology by showing the importance of facilitating conditions, social influence, and habit. Farmers did not adopt technology only because they had positive attitudes. They needed affordable access, technical support, stable infrastructure, and social proof from trusted actors. This is consistent with Larasati et al. (2024), who found that farmer readiness in West Java was shaped by performance expectancy, facilitating conditions, personal innovativeness, and habits of farm recording. The present study deepens that insight by showing how these factors operate in daily farming life. For example, facilitating conditions included not only internet access and devices, but also extension assistance, group leaders, family members, and cooperative-based support.

The results are also consistent with research on social and cultural determinants of precision agriculture adoption. John et al. (2023) found that social dynamics, awareness, knowledge pathways, and cultural norms strongly affect adoption among small-scale farmers. Kendall et al. (2022) similarly showed that family farmers' decisions are shaped by farming culture, local challenges, and practical support mechanisms. This study confirms those findings in the Indonesian smallholder context. Farmers preferred to learn through collective spaces, demonstrations, and peer experience. Adoption became more acceptable when the technology entered existing social structures, especially farmer groups, cooperatives, and extension networks.

The study also supports previous findings on financial constraints and the need for alternative access models. Miine et al. (2023) found that access to credit and farmer organization membership increased adoption of digital agricultural services among smallholder farmers. Khaspuria et al. (2024) also stressed that financial barriers, limited capital, inadequate infrastructure, and technical knowledge gaps remain major obstacles to precision agriculture adoption. The present findings show that smallholder farmers may not need to own every technology individually. Shared ownership, service rental, cooperative-based access, and group-managed tools can create more realistic adoption pathways. This finding is important because many adoption programs still assume that farmers will adopt technology as individual buyers.

The findings also offer a critical perspective on the relationship between digital technology and local knowledge. Van der Velden et al. (2023) argue that farmers integrate precision agriculture data with embodied and ecological knowledge. This study confirms that farmers did not want technology to replace their experience. They wanted technology to strengthen their judgment. Farmers accepted digital tools when they could compare sensor data, drone images, or application recommendations with their own knowledge of soil, rainfall, pests, and crop growth. This finding challenges a purely technology-driven approach to precision agriculture. It suggests that adoption strategies should treat farmers as knowledge holders, not only as technology users.

The role of demonstration and visual evidence also confirms findings from McCarthy et al. (2023), who showed that drone data helped smallholder farmers understand farm conditions and make more informed decisions. In this study, farmers trusted technology more when they saw local evidence from demonstration plots, peer users, or visual outputs. This implies that training should not rely only on classroom-style explanation. It should use field demonstrations, before-after comparisons, farmer testimonials, and simple visual interpretation. This approach can reduce uncertainty and help farmers understand the economic and practical value of precision agriculture.

The findings have several theoretical implications. First, they show that technology adoption theory needs stronger attention to local context, collective trust, and embodied knowledge. Perceived usefulness, ease of use, and facilitating conditions remain important, but they should be interpreted through farmers' lived realities. Second, the study suggests that adoption is not a single decision. It is a gradual process of awareness, observation, trial, negotiation, adaptation, and continued use. Third, the findings show that local institutions such as farmer groups and cooperatives can act as adoption intermediaries. These institutions can reduce risk, support learning, and create shared access to technology.

The practical implications are also clear. Local governments and agricultural extension agencies should design adoption programs that begin with farmers' priority problems, not with technology promotion. Training should be practical, repeated, and field-based. Technology providers should simplify interfaces, use local language, and offer after-sales support. Farmer groups and cooperatives should be involved in managing shared technology services. Subsidies should prioritize technologies with direct relevance to smallholder needs, such as irrigation sensors, pest monitoring, weather advisories, drone-based mapping, and fertilizer efficiency tools. Extension officers also need specific training in digital agriculture so they can support farmers during early adoption and troubleshooting.

Future research can expand this study in several ways. First, comparative studies across different regions and commodities can explain how local context shapes adoption differently. Second, longitudinal research can examine how farmers move from first exposure to sustained use. Third, mixed-methods studies can combine qualitative findings with survey-based measurement of adoption readiness, technology use intensity, and farm-level outcomes. Fourth, future studies can examine gender, age, and youth involvement in precision agriculture adoption because digital technology often enters farming households through younger family members. These directions can strengthen understanding of how precision agriculture can become more inclusive, affordable, and locally relevant for smallholder farmers.

4. Conclusions

This study concludes that the adoption of precision agriculture technologies among smallholder farmers is shaped by the interaction between perceived usefulness, affordability, trust, digital literacy, institutional support, and local farming knowledge. Farmers accepted technology when they could see clear benefits for irrigation, fertilizer efficiency, pest control, weather anticipation, and labor reduction. However, high costs, limited technical skills, weak infrastructure, and uncertainty about long-term benefits remained major barriers. The findings show that adoption is not only a technical decision, but also a social and contextual process influenced by farmer groups, extension officers, peer experience, demonstration plots, and local trust networks.

The study contributes to the literature on agricultural technology adoption by emphasizing the importance of local context, collective learning, and the integration of digital tools with farmers' embodied knowledge. Practically, the findings suggest that adoption programs should prioritize field-based training, shared technology access, cooperative-based service models, simple digital interfaces, and continuous extension support. From a policy perspective, local governments should support affordable financing, rural digital infrastructure, and capacity building for extension officers. Future research should compare different regions, commodities, and farmer groups to deepen understanding of how local social, economic, and cultural conditions shape sustained adoption of precision agriculture technologies.

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