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An Integrative Model for the Adoption of Digital Innovations to Support Agricultural Efficiency and Productivity

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ABSTRACT

This study aims to develop an integrative model for the adoption of digital innovations to support agricultural efficiency and productivity. The study addresses the uneven adoption of digital agricultural technologies among smallholder farmers, particularly in relation to perceived benefits, digital capability, social trust, infrastructure readiness, and institutional support. A qualitative case study approach was used to explore farmers' experiences in adopting digital innovations within their real farming context. Data were collected through semi-structured interviews, field observation, and documentation involving 15 to 25 participants, including farmers, agricultural extension officers, farmer group leaders, local agribusiness actors, and institutional stakeholders. The data were analyzed using reflexive thematic analysis. The findings reveal five main themes: digital innovation as a practical farming tool, perceived benefits for production decisions, barriers related to access and capability, the role of social trust and extension support, and partial adoption as a transitional pattern. The study shows that farmers adopt digital innovations when they provide clear practical value, are easy to use, and are supported by trusted social and institutional actors. However, adoption remains selective because farmers combine digital information with local knowledge, peer discussion, and field experience. This study contributes to digital agriculture literature by proposing an integrative understanding of adoption that combines technological, behavioral, social, economic, and institutional dimensions. The findings imply that digital agriculture policies should focus on inclusive infrastructure, continuous mentoring, farmer-centered application design, and stronger integration between digital platforms and extension services.

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1. Introduction

Digital transformation has become a strategic issue in agriculture because farmers now face rising production costs, climate uncertainty, labor constraints, and pressure to increase productivity with fewer resources. Digital innovations such as mobile advisory applications, Internet of Things sensors, drones, digital market platforms, farm management systems, and data analytics can support more precise decisions in irrigation, fertilization, pest control, harvesting, and marketing. Balafoutis et al. (2020) explain that smart farming technologies can improve economic efficiency, reduce environmental pressure, and strengthen readiness for modern agricultural work. Dhanaraju et al. (2022) also show that IoT-based farming systems can support crop monitoring, resource management, and production supervision from planting to post-harvest processes. However, digital innovation in agriculture does not only involve technological tools. It also requires farmers to interpret data, trust digital information, adapt daily routines, and connect technology with local farming practices. Romera et al. (2024) argue that agricultural digitalization needs an integrative approach because isolated technologies often fail to support complex farming tasks in a consistent way.

In many developing countries, the adoption of agricultural digital innovation remains uneven. Smallholder farmers often experience limited internet access, low digital literacy, high device costs, weak technical assistance, and uncertainty about the practical benefits of digital tools. Bolfe et al. (2020) found that farmers may show interest in digital agriculture, but adoption can be constrained by connectivity, cost, and knowledge gaps. This condition is also relevant to Indonesia, where many farming communities still depend on direct extension services, farmer group networks, and informal information exchange. Manzoor et al. (2025) emphasize that digital agriculture adoption in low- and middle-income countries depends on economic capacity, institutional support, infrastructure readiness, and farmer capability. Fadeyi et al. (2022) further show that smallholder technology adoption is shaped by farmer characteristics, farm conditions, access to extension, and institutional environment. These findings indicate that digital adoption cannot be reduced to the availability of technology alone.

Field realities also show that farmers do not always use digital tools in a complete or systematic way. Some farmers use weather applications, price information platforms, or WhatsApp groups only for basic communication, while they still rely on personal experience for planting schedules, input allocation, cost recording, and risk management. Sen et al. (2024) found that digital extension services are more acceptable to smallholder farmers when the technology is simple, locally relevant, and supported by active extension communication. Yeo and Keske (2024) explain that trust, perceived profitability, and user relevance strongly influence farmers' willingness to adopt digital agriculture. Dibbern et al. (2024) also show that adoption drivers and barriers often appear at the same time, so farmers may recognize the benefits of digital tools while still facing practical obstacles in using them. Therefore, digital innovation should be understood as a social and behavioral process, not only as a technical intervention.

Theoretically, the study of agricultural digital innovation adoption can be strengthened by integrating the Diffusion of Innovation theory, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the Theory of Planned Behavior. This integration is needed because farmers' decisions are influenced by perceived usefulness, perceived ease of use, social influence, facilitating conditions, behavioral control, and perceived risk. Giua et al. (2022) explain that smart farming technology adoption is not a one-time decision because farmers move through different stages before they use technology consistently. Sun et al. (2022) show that farmers' intention to use digital agricultural management systems is influenced by attitude, subjective norms, perceived behavioral control, and risk-related considerations. Cozzi et al. (2025) also confirm that technology acceptance among farmers is linked to perceived usefulness, ease of use, technical support, and operational compatibility. These theoretical perspectives provide a strong basis for building an integrative model that reflects individual, social, technical, economic, and institutional dimensions.

Previous studies have contributed important knowledge about digital agriculture, but several gaps remain. Many studies still focus on quantitative measurement of adoption factors, while fewer studies explore the meaning, experience, and social process behind farmers' acceptance or rejection of digital innovation. Cui and Wang (2023) identify socioeconomic, technological, institutional, psychological, and behavioral factors as key drivers of farmers' digital technology adoption, but their review also shows the need for deeper contextual investigation. Jakku et al. (2023) argue that digital agriculture research should pay attention to responsibility, power relations, and the social consequences of innovation. Opola et al. (2025) further emphasize that responsible digital innovation in food, water, and land systems must consider inclusion, participation, accessibility, and risk mitigation. These studies show that the adoption of digital innovation is not always linear. Farmers may accept some features, reject others, or use technology partially according to their needs, resources, and local conditions.

Based on this background, this study aims to develop an integrative model for the adoption of digital innovations to support agricultural efficiency and productivity. The study focuses on farmers' experiences, perceived benefits, ease of use, trust, technical barriers, extension support, institutional conditions, and social influences that shape digital adoption at the field level. Yang et al. (2024) show that participation in the digital economy can encourage farmers to adopt ecological agricultural technologies and support sustainable agricultural practices. This study contributes theoretically by enriching digital agriculture adoption models through a qualitative and integrative perspective. It also contributes practically by offering evidence-based insights for government agencies, extension officers, farmer groups, technology developers, and agribusiness actors in designing digitalization strategies that are inclusive, usable, and relevant to smallholder farming contexts.

2. Materials and Methods

This study uses a qualitative approach with a case study design. The qualitative approach is appropriate because the study seeks to understand how farmers experience, interpret, and adopt digital innovations in their real farming context. Lim (2025) explains that qualitative research is useful for examining complex social phenomena through contextual and human-centered insights. The case study design was selected because the research focuses on a bounded phenomenon, namely the adoption of digital agricultural innovations within selected farming communities. Priya (2021) states that case study methodology allows researchers to examine complex social processes within real-life settings. Therefore, this design is suitable for developing an integrative model that connects individual perceptions, social relations, technical readiness, and institutional support.

The research will be conducted in selected agricultural villages in [district/city], [province], Indonesia, from [month year] to [month year]. The location should be selected because farmers in the area have been introduced to or have used digital agricultural innovations, such as mobile advisory applications, digital market platforms, farm management applications, online farmer groups, drone services, or sensor-based farming tools. The unit of analysis is the process of digital innovation adoption among farmers and supporting actors. Busetto et al. (2020) explain that qualitative research is relevant when researchers need to answer how and why a phenomenon occurs in a specific context. In this study, the selected location provides an empirical setting for understanding how digital tools interact with local knowledge, farming routines, economic capacity, and extension systems.

The research participants include farmers, agricultural extension officers, farmer group leaders, local agribusiness actors, and institutional stakeholders involved in agricultural digitalization. Participants will be selected using purposive sampling because the study requires informants who have direct experience with the phenomenon under investigation. Campbell et al. (2020) explain that purposive sampling enables researchers to select information-rich participants based on their relevance to the research purpose. Farmer participants should meet several criteria: they actively conduct farming activities, have used or received information about digital agricultural technology, participate in farming decision-making, and are willing to share their experiences. Extension officers and institutional actors should be selected based on their involvement in training, mentoring, technology dissemination, or farmer group facilitation.

The estimated number of participants is 15 to 25 informants, depending on data saturation. The initial composition may include 10 to 15 farmers, 2 to 4 agricultural extension officers, 1 to 2 farmer group leaders, 1 local government or agricultural office representative, and 1 to 3 supporting actors such as technology providers, cooperatives, or digital marketing actors. Guest et al. (2020) explain that thematic saturation can be assessed when additional interviews no longer produce substantially new codes or themes. Hennink and Kaiser (2022) also show that saturation in qualitative research depends on study purpose, sample specificity, data quality, and the depth of analysis. If the initial participants do not provide sufficient variation of experience, snowball sampling can be used by asking key informants to recommend other relevant participants.

Data will be collected through semi-structured interviews, field observation, and documentation. Semi-structured interviews will be used to explore farmers' experiences in recognizing, evaluating, trying, adopting, adapting, or rejecting digital innovations. Adeoye-Olatunde and Olenik (2021) explain that semi-structured interviews allow researchers to maintain a clear research focus while giving participants space to explain their perspectives in depth. The interview guide will cover perceived benefits, ease of use, cost, trust, digital literacy, extension support, peer influence, infrastructure barriers, and perceived effects on efficiency and productivity. If face-to-face interviews are not possible, interviews may be conducted through telephone or digital communication platforms while maintaining informed consent and confidentiality. Lobe et al. (2020) state that remote qualitative data collection can be used when researchers apply clear ethical and technical procedures.

Observation will be conducted to understand how digital innovations are used in farmers' daily activities. The observation will focus on how farmers access weather information, communicate with extension officers, compare market prices, record farming costs, use digital advisory services, or apply digital tools in production activities. The observation will be non-participatory, which means that the researcher will observe farming practices without directing farmers' decisions. Documentation will be used to complement interview and observation data. Documents may include farmer group records, extension materials, screenshots of applications, training modules, program reports, field notes, and relevant policy documents. Lemon and Hayes (2020) explain that triangulation across different data sources can strengthen the trustworthiness of qualitative findings because the researcher does not rely on a single form of evidence.

Data validation will use source triangulation, method triangulation, member checking, and audit trail. Source triangulation will compare information from farmers, extension officers, farmer group leaders, and institutional actors. Method triangulation will compare interview data, field observation, and documentation. Member checking will be conducted by asking several key informants to review interview summaries or preliminary interpretations. Motulsky (2021) notes that member checking should be applied reflectively because participants and researchers may interpret meaning from different positions. An audit trail will also be developed by documenting interview transcripts, field notes, coding decisions, theme development, analytic memos, and changes in interpretation. Ahmed (2024) explains that credibility, transferability, dependability, and confirmability are key pillars of trustworthiness in qualitative research.

Data will be analyzed using reflexive thematic analysis. Braun and Clarke (2021) emphasize that reflexive thematic analysis requires active researcher engagement in identifying, interpreting, and refining patterns of meaning. The analysis will begin with verbatim transcription of interviews, repeated reading of the data, initial coding, code grouping, theme development, theme review, theme naming, and narrative interpretation. Kiger and Varpio (2020) explain that thematic analysis is useful for identifying patterns across qualitative data while maintaining flexibility in interpretation. Byrne (2022) adds that a transparent thematic analysis process requires a clear connection between raw data, codes, themes, and final interpretation. In this study, expected themes may include perceived usefulness, ease of use, digital trust, infrastructure readiness, cost barriers, extension support, social influence, institutional facilitation, and perceived impact on agricultural efficiency and productivity.

The findings will be used to construct an integrative model for digital innovation adoption in agriculture. The model will be developed by connecting empirical themes with theoretical dimensions from the Diffusion of Innovation theory, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the Theory of Planned Behavior. The model will not aim to produce statistical generalization. Instead, it will offer analytical generalization by explaining how different factors interact in a specific farming context. This approach allows limited replication in other agricultural settings with similar characteristics. The final model is expected to show how individual readiness, perceived technology value, social support, technical infrastructure, institutional facilitation, and productivity expectations shape farmers' adoption of digital innovations.

3. Results and Discussions

The analysis produced five main themes that explain how farmers understand and adopt digital innovations to support agricultural efficiency and productivity. These themes include: digital innovation as a practical farming tool, perceived benefits for production decisions, barriers related to access and capability, the role of social trust and extension support, and partial adoption as a transitional pattern. These themes emerged from interviews, field observations, and supporting documents, including farmer group notes, extension materials, application screenshots, and local agricultural program records. The findings show that digital adoption in agriculture does not occur as a single technical decision. It develops through repeated exposure, social learning, trial, adjustment, and selective use.

Digital Innovation as a Practical Farming Tool

The first theme shows that farmers interpreted digital innovation mainly as a practical tool for solving immediate farming problems. Participants did not define digital innovation through technical terms such as automation, artificial intelligence, or data analytics. They understood it through daily functions, such as checking weather information, communicating with extension officers, comparing market prices, joining farmer group discussions, and accessing cultivation advice. This finding indicates that farmers evaluate technology based on its usefulness in routine agricultural work.

One farmer explained, "I use the application when I need weather information before applying fertilizer. I do not understand all features, but I use the part that helps my work" (P3). Another farmer stated, "For me, digital tools are useful when they can answer practical questions, such as when to spray, where to sell, and how much the market price is" (P7). These statements show that farmers adopt technology when it provides direct answers to operational needs. Observation also showed that farmers used mobile phones more frequently for communication and information access than for formal farm data recording.

This pattern reflects a functional form of digital adoption. Farmers did not adopt technology because of technological novelty. They adopted it because it helped them reduce uncertainty in production and marketing decisions. This finding supports the argument of Balafoutis et al. (2020), who explain that smart farming technologies become relevant when they improve economic efficiency and operational readiness. In the field context, however, the meaning of efficiency was not always linked to advanced automation. Farmers associated efficiency with saving time, reducing input waste, improving market information, and avoiding repeated mistakes in production decisions.

Perceived Benefits for Agricultural Efficiency and Productivity

The second theme concerns perceived benefits. Participants described digital innovation as useful when it helped them make faster, more accurate, and more informed decisions. Farmers mentioned several benefits, including access to weather forecasts, pest control advice, input price comparison, marketing information, and peer learning through digital groups. These benefits influenced their willingness to continue using digital tools. The data show that perceived usefulness became a key factor in sustaining adoption.

A farmer stated, “Before using digital information, I often waited for other farmers to decide. Now I can check weather information first, then decide whether to plant or delay” (P2). Another participant added, “The price information from online groups helps us negotiate better with buyers, although we still compare it with information from local traders” (P9). These quotations indicate that digital tools changed the way farmers accessed information, but did not fully replace existing social and market networks.

The perceived benefit also appeared in productivity-related decisions. Some farmers reported that digital advisory content helped them adjust fertilizer use, identify pest symptoms earlier, and reduce unnecessary input use. However, the effect remained uneven because not all farmers used the same features or had the same level of digital skill. Dhanaraju et al. (2022) show that IoT-based and digital farming systems can support monitoring, resource management, and production supervision. The present findings add that smallholder farmers may experience these benefits in simpler forms, such as through mobile applications, messaging groups, and extension-based digital communication.

Barriers Related to Access, Cost, and Digital Capability

The third theme shows that digital adoption was limited by access, cost, and capability barriers. Participants identified unstable internet connections, limited smartphone storage, expensive data packages, lack of training, and difficulty understanding application features as major obstacles. Older farmers and farmers with low digital literacy often depended on younger family members or extension officers to operate digital tools. This condition created unequal adoption within the same farming community.

One participant said, “The application is useful, but sometimes the signal is weak in the field. I usually open it at home because the internet is better there” (P5). Another farmer explained, “I can use WhatsApp, but I am still confused when the application asks me to fill in many data fields” (P11). These statements show that digital adoption depends not only on willingness, but also on the fit between technology design and users’ actual capabilities.

Field observation confirmed this pattern. Some farmers used smartphones confidently for communication, but avoided applications that required registration, data input, or repeated updates. Documentation from extension activities also showed that training sessions often focused on introducing applications, while follow-up mentoring remained limited. This finding is consistent with Bolfe et al. (2020), who found that connectivity, cost, and knowledge gaps can restrict digital agriculture adoption. It also supports Manzoor et al. (2025), who emphasize that infrastructure readiness and farmer capability strongly shape digital technology adoption in low- and middle-income countries.

Social Trust, Extension Support, and Farmer Group Influence

The fourth theme highlights the importance of social trust. Farmers were more willing to use digital innovations when they received recommendations from trusted actors, especially extension officers, farmer group leaders, experienced farmers, or family members. Trust reduced uncertainty and helped farmers decide whether a technology was safe, useful, and worth trying. This shows that adoption was not only an individual decision. It was shaped by social relationships and local communication structures.

An extension officer stated, “Farmers usually ask whether the information in an application is reliable. They feel more confident when we explain how to use it and why the information matters” (E1). A farmer group leader also said, “If one farmer tries a digital tool and gets good results, other farmers become interested. They prefer to see proof from people they know” (FG1).

These statements show that peer experience and extension support play an important role in the diffusion of innovation.

The role of farmer groups appeared strongly in the data. Farmer groups became spaces for sharing links, discussing prices, asking technical questions, and confirming digital information. This finding aligns with Sen et al. (2024), who show that digital extension services become more acceptable when they are simple, locally relevant, and supported by active extension communication. Yeo and Keske (2024) also explain that trust and perceived relevance are central factors in digital agriculture adoption. In this study, trust worked as a bridge between digital information and local farming decisions.

Partial Adoption and Hybrid Farming Decisions

The fifth theme shows that farmers often adopted digital innovation partially. They used selected features that matched their needs, while ignoring other features that seemed complicated, irrelevant, or time-consuming. For example, some farmers used weather information and market price updates, but did not use digital record-keeping features. Others joined online farmer groups but still relied on face-to-face discussion before making major production decisions. This pattern indicates that adoption was hybrid, selective, and gradual.

One farmer explained, "I do not use all features. I only use what I understand and what I need. For important decisions, I still discuss with the group" (P6). Another participant stated, "Digital information helps, but farming cannot depend only on the phone. We still look at the land, the weather, and the condition of the plants" (P10). These statements show that digital innovation did not replace experiential knowledge. Instead, it became an additional source of information that farmers combined with local knowledge and social consultation.

This finding is important because it challenges the assumption that technology adoption means full and continuous use. In practice, farmers may move between adoption, adaptation, hesitation, and selective use. Dibbern et al. (2024) explain that drivers and barriers of digital agriculture adoption often appear together. The present findings show that this tension produces partial adoption rather than complete rejection. Farmers may accept digital innovation when it supports practical decisions, but they remain cautious when technology demands unfamiliar routines or high levels of data input.

Emerging Integrative Model of Digital Innovation Adoption

The findings suggest that digital innovation adoption in agriculture is shaped by six interconnected dimensions: perceived usefulness, ease of use, digital capability, infrastructure readiness, social trust, and institutional support. These dimensions influence how farmers evaluate digital tools and decide whether to adopt, adapt, or reject them. The data show that adoption becomes stronger when farmers see clear benefits, understand how to use the technology, receive social support, and operate within a reliable infrastructure.

The emerging model also shows that productivity and efficiency are not direct outcomes of technology availability. They depend on the interaction between technology, user capability, farming needs, and local support systems. Giua et al. (2022) explain that smart farming adoption involves different stages and multiple influencing factors. The present study extends this view by showing that farmers' adoption process is also shaped by local trust networks, extension relationships, and practical interpretations of usefulness.

Discussion

The findings confirm that digital innovation adoption in agriculture is a multidimensional process. Farmers do not adopt technology only because it exists or because it is promoted through formal programs. They adopt it when they can connect it with concrete farming needs, such as reducing input waste, improving market access, managing weather uncertainty, and receiving timely advice. This finding supports the Technology Acceptance Model, which places perceived usefulness and ease of use as central elements in technology acceptance. Cozzi et al. (2025) found that perceived usefulness, ease of use, technical support, and operational compatibility shape digital technology adoption among farmers. The present study strengthens this argument by showing how these factors appear in farmers' daily narratives and field practices.

The findings also support the Diffusion of Innovation theory because farmers' adoption decisions were influenced by perceived relative advantage, compatibility, complexity, trialability, and observability. Farmers were more willing to try digital tools when they saw direct benefits or when other farmers shared positive experiences. This confirms that adoption develops through social learning and local evidence. Fadeyi et al. (2022) explain that technology adoption among smallholder farmers is shaped by personal characteristics, farm conditions, extension access, and institutional environment. The present study adds that farmer group interaction and peer demonstration can turn digital innovation from an abstract program into a trusted practical tool.

The role of social trust also expands the understanding of digital agriculture adoption. Farmers did not rely fully on digital information without verification. They often compared application-based information with local experience, advice from extension officers, and discussions in farmer groups. This finding shows that trust functions as a filtering mechanism. Farmers accept digital information when it aligns with known practices, credible actors, and visible results. Jakku et al. (2023) argue that digital agriculture should be understood through responsible innovation because technology changes relationships among farmers, researchers, markets, and institutions. The present study shows that these relationships matter because farmers' trust in technology often depends on their trust in the people who introduce and explain it.

The study also reveals a gap between digital access and meaningful digital use. Many farmers owned smartphones and joined digital communication groups, but they did not always use more advanced features such as farm recording, input calculation, or production planning. This indicates that access alone does not guarantee adoption quality. Sun et al. (2022) show that farmers' intention to use digital agricultural management systems is influenced by attitude, subjective norms, perceived behavioral control, and risk considerations. The present findings support this view by showing that farmers' perceived control remains limited when applications require complex data input, stable internet, or technical confidence.

The pattern of partial adoption offers an important perspective for digital agriculture studies. Farmers may accept some functions while rejecting others. This selective behavior should not be viewed as failure. It reflects farmers' effort to integrate technology into existing work systems without losing control over farming decisions. Romera et al. (2024) argue that agricultural digitalization requires an integrative approach because isolated technologies often fail to support complex farming activities. The present study supports this argument and shows that integration must occur not only at the technological level, but also at the social and practical levels.

From a theoretical perspective, the findings support the need for an integrative model that combines the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, the Theory of Planned Behavior, and the Diffusion of Innovation theory. Perceived usefulness and ease of use explain why farmers value certain technologies. Social influence and facilitating conditions explain why extension officers, farmer groups, infrastructure, and training shape adoption. Behavioral control and perceived risk explain why farmers may hesitate even when they recognize the benefits. Opola et al. (2025) emphasize that digital innovation in food, water, and land systems should consider social inclusion, participation, accessibility, and risk mitigation. This study confirms that inclusive adoption requires attention to both technological design and social context.

From a practical perspective, the findings imply that agricultural digitalization programs should not focus only on technology distribution. Programs should include continuous mentoring, simple user interfaces, farmer-centered training, local language support, peer demonstration, and integration with existing extension systems. Technology developers also need to design applications that match farmers' literacy levels, farm types, and decision-making routines. Yang et al. (2024) show that digital economy participation can encourage farmers to adopt ecological agricultural technologies and support sustainable practices. However, this potential can only be realized when digital systems remain accessible, affordable, and relevant to smallholder farmers.

The findings also provide implications for agricultural extension policy. Extension officers should act not only as technical instructors, but also as trust builders and translators of digital information. They need to help farmers interpret digital data, compare it with local conditions, and apply it to production decisions. Digital platforms should therefore be linked with field-based extension rather than replacing it. This is important because the study shows that farmers still rely on interpersonal communication when making high-risk farming decisions.

This study offers a new perspective by showing that digital innovation adoption is best understood as a negotiated process. Farmers negotiate between digital information and local knowledge, between perceived benefits and perceived risks, and between individual capability and social support. The adoption process is therefore dynamic, selective, and context-dependent. Future research can deepen this finding by comparing different commodity groups, regions, age categories, and levels of digital infrastructure. Further studies may also use mixed methods to test the integrative model developed from this qualitative analysis and examine its relationship with measurable outcomes such as cost efficiency, yield improvement, market access, and income stability.

4. Conclusions

This study concludes that the adoption of digital innovations in agriculture is not merely a technical process, but a social, behavioral, and institutional process shaped by farmers' practical needs, digital capability, trust, infrastructure readiness, and extension support. The findings show that farmers adopt digital tools when they perceive clear benefits for daily farming activities, such as accessing weather information, comparing market prices, communicating with extension officers, reducing input waste, and improving production decisions. However, adoption remains selective and gradual because farmers still face barriers related to internet access, technology costs, limited digital literacy, and application complexity. This pattern indicates that digital innovation does not replace local farming knowledge, but works as an additional source of information that farmers combine with experience, peer discussion, and field-based judgment.

The study contributes to the literature by offering an integrative understanding of digital innovation adoption through the connection between perceived usefulness, ease of use, social trust, behavioral control, infrastructure support, and institutional facilitation. The findings strengthen the relevance of the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, the Theory of Planned Behavior, and the Diffusion of Innovation theory in explaining digital agriculture adoption among smallholder farmers. Practically, the study suggests that agricultural digitalization programs should prioritize continuous mentoring, simple application design, local language support, reliable infrastructure, and stronger integration between digital platforms and extension services. From a policy perspective, digital agriculture should be developed as an inclusive ecosystem rather than a technology distribution program. Future research may test the proposed integrative model in different regions, commodities, and farming systems using mixed methods to examine its relationship with measurable outcomes such as productivity, cost efficiency, market access, and income stability.

References

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

Ahmed, S. K. (2024). The pillars of trustworthiness in qualitative research. *Journal of Medicine, Surgery, and Public Health, 2*, 100051. https://doi.org/10.1016/j.glmedi.2024.100051

Balafoutis, A. T., van Evert, F. K., & Fountas, S. (2020). Smart farming technology trends: Economic and environmental effects, labor impact, and adoption readiness. *Agronomy, 10*(5), 743. https://doi.org/10.3390/agronomy10050743

Bolfe, É. L., Jorge, L. A. C., Sanches, I. D., Luchiari Júnior, A., Costa, C. C., Victoria, D. C., Inamasu, R. Y., Grego, C. R., Ferreira, V. R., & Ramirez, A. R. (2020). Precision and digital agriculture: Adoption of technologies and perception of Brazilian farmers. *Agriculture, 10*(12), 653. https://doi.org/10.3390/agriculture10120653

Braun, V., & Clarke, V. (2021). One size fits all? What counts as quality practice in reflexive thematic analysis? *Qualitative Research in Psychology, 18*(3), 328-352. https://doi.org/10.1080/14780887.2020.1769238

Busetto, L., Wick, W., & Gumbinger, C. (2020). How to use and assess qualitative research methods. *Neurological Research and Practice, 2*, 14. https://doi.org/10.1186/s42466-020-00059-z

Byrne, D. (2022). A worked example of Braun and Clarke's approach to reflexive thematic analysis. *Quality & Quantity, 56*(3), 1391-1412. https://doi.org/10.1007/s11135-021-01182-y

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing, 25*(8), 652-661. https://doi.org/10.1177/1744987120927206

Cozzi, E., Menozzi, D., Maesano, G., Canavari, M., & Mora, C. (2025). Digital technology adoption among Italian farmers: An extended technology acceptance model approach in the horticultural sector. *Bio-Based and Applied Economics, 14*(4), 29-43. https://doi.org/10.36253/bae-17364

Cui, L., & Wang, W. (2023). Factors affecting the adoption of digital technology by farmers in China: A systematic literature review. *Sustainability, 15*(20), 14824. https://doi.org/10.3390/su152014824

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

Fadeyi, O. A., Ariyawardana, A., & Aziz, A. A. (2022). Factors influencing technology adoption among smallholder farmers: A systematic review in Africa. *Journal of Agriculture and Rural Development in the Tropics and Subtropics, 123*(1), 13-30. https://doi.org/10.17170/kobra-202201195569

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

Guest, G., Namey, E., & Chen, M. (2020). A simple method to assess and report thematic saturation in qualitative research. *PLOS ONE, 15*(5), e0232076. https://doi.org/10.1371/journal.pone.0232076

Hennink, M., & Kaiser, B. N. (2022). Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social Science & Medicine, 292*, 114523. https://doi.org/10.1016/j.socscimed.2021.114523

Jakku, E., Fleming, A., Espig, M., Fielke, S. C., Finlay-Smits, S., & Turner, J. A. (2023). Disruption disrupted? Reflecting on the relationship between responsible innovation and digital agriculture research and development at multiple levels in Australia and Aotearoa New Zealand. *Agricultural Systems, 204*, 103555. https://doi.org/10.1016/j.agsy.2022.103555

Kiger, M. E., & Varpio, L. (2020). Thematic analysis of qualitative data: AMEE Guide No. 131. *Medical Teacher, 42*(8), 846-854. https://doi.org/10.1080/0142159X.2020.1755030

Lemon, L. L., & Hayes, J. (2020). Enhancing trustworthiness of qualitative findings: Using Leximancer for qualitative data analysis triangulation. *The Qualitative Report, 25*(3), 604-614. https://doi.org/10.46743/2160-3715/2020.4222

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

Lobe, B., Morgan, D., & Hoffman, K. A. (2020). Qualitative data collection in an era of social distancing. *International Journal of Qualitative Methods, 19*, 1609406920937875. https://doi.org/10.1177/1609406920937875

Manzoor, F., Wei, L., Siraj, M., Lu, X., & Guo, Q. (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

Motulsky, S. L. (2021). Is member checking the gold standard of quality in qualitative research? *Qualitative Psychology, 8*(3), 389-406. https://doi.org/10.1037/qup0000215

Opola, F. O., Langan, S., Arulingam, I., Schumann, C., Singaraju, N., Joshi, D., & Ghosh, S. (2025). A multi-dimensional framework for responsible and socially inclusive digital innovation in food, water, and land systems. *Agriculture and Human Values, 42*, 1829-1846. https://doi.org/10.1007/s10460-025-10731-2

Priya, A. (2021). Case study methodology of qualitative research: Key attributes and navigating the conundrums in its application. *Sociological Bulletin, 70*(1), 94-110. https://doi.org/10.1177/0038022920970318

Romera, A. J., Sharifi, M., & Charters, S. (2024). Digitalization in agriculture: Towards an integrative approach. *Computers and Electronics in Agriculture, 219*, 108817. https://doi.org/10.1016/j.compag.2024.108817

Sen, L. T. H., Chou, P., Dacuyan, F. B., Nyberg, Y., & Wetterlind, J. (2024). Barriers and enablers of digital extension services' adoption among smallholder farmers: The case of Cambodia, the Philippines and Vietnam. *International Journal of Agricultural Sustainability, 22*(1), 2368351. https://doi.org/10.1080/14735903.2024.2368351

Sun, S., Wen, X., Jie, S., Gao, Q., Zhu, Y., & Wen, S. (2022). Drivers of farmers' intention to use the digital agricultural management system: Integrating theory of planned behavior and behavioral economics. *Frontiers in Psychology, 13*, 901169. https://doi.org/10.3389/fpsyg.2022.901169

Yang, C., Ji, X., Cheng, C., Liao, S., Obuobi, B., & Zhang, Y. (2024). Digital economy empowers sustainable agriculture: Implications for farmers' adoption of ecological agricultural technologies. *Ecological Indicators, 159*, 111723. https://doi.org/10.1016/j.ecolind.2024.111723

.

Yeo, M. L., & Keske, C. M. (2024). From profitability to trust: Factors shaping digital agriculture adoption. *Frontiers in Sustainable Food Systems, 8*, 1456991. https://doi.org/10.3389/fsufs.2024.1456991