Global Journal of Agricultural Engineering
Vol. 1 No.1 2026 Page 30-37
E-ISSN: XXXX-XXXX, DOI: 10.XXXXX/XXXX

Smart Farming Technology Adoption Models to Improve Productivity and Water Efficiency

Sari Maulana[1]*, Taufik Kurniawan[2], Utami Firmansyah[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 : 28 January 2026
Revised : 31 March 2026
Accepted : 18 April 2026

Keyword:

Smart Farming Technology;
Technology Adoption;
Water Efficiency;
Agricultural Productivity.

ABSTRACT

This study aims to explore smart farming technology adoption models for improving agricultural productivity and water efficiency. The issue was examined because many smallholder farmers still face limited capital, low digital literacy, uncertain water availability, and uneven access to technical support. This study used a qualitative case study approach to understand farmers' experiences, meanings, and decision-making processes in adopting smart farming technologies. Data were collected through semi-structured interviews, field observation, and documentation involving farmers, agricultural extension officers, farmer group leaders, irrigation actors, and technology facilitators selected through purposive and snowball sampling. The data were analyzed using thematic analysis supported by source triangulation, method triangulation, member checking, and audit trail procedures. The findings show five main themes: perceived usefulness for water efficiency, productivity as the main adoption motive, cost and technical skill as adoption barriers, social influence and extension support, and partial adaptive adoption. The study found that farmers did not simply accept or reject smart farming. They adjusted technology based on land size, crop type, water access, financial capacity, and local farming routines. These findings contribute to technology adoption theory by showing that smart farming adoption is a contextual social process, not only an individual technological decision. The study implies that policy and practice should support affordable technology, farmer-centered training, demonstration plots, and stronger institutional assistance. Future research should test adaptive adoption models across different agricultural contexts.

***) Corresponding Author:**

Sari Maulana,
Department of Agribusiness, Faculty of Agriculture, IPB University, Bogor, Indonesia
Email: sari.maulana105@gmail.com

1. Introduction

Global agriculture is facing increasing pressure to produce more food with fewer natural resources. Climate variability, declining water availability, rising production costs, and unstable crop yields have pushed farmers, governments, and technology providers to search for more adaptive farming systems. Smart farming offers one possible response because it integrates sensors, Internet of Things devices, artificial intelligence, remote sensing, automated irrigation, and decision-support platforms into daily farm management. These technologies can help farmers monitor soil moisture, crop growth, pest risk, and water use more accurately. Balafoutis et al. (2020) show that smart farming technologies can improve economic efficiency, environmental performance, and labor productivity. However, their benefits depend on whether farmers can understand, access, trust, and operate the technology within their real farming conditions.

In Indonesia and other developing agricultural economies, the adoption of smart farming remains uneven. Many farmers still manage land through experience-based decisions, seasonal routines, and advice from peers or extension officers. This practice does not mean that farmers reject innovation. Instead, it shows that technology adoption takes place within social, economic, and cultural contexts. Smallholder farmers often face limited capital, weak digital infrastructure, low technical assistance, and uncertainty about the practical value of new tools. Studies on digital agriculture in low- and middle-income countries show that adoption depends on affordability, perceived usefulness, digital literacy, institutional support, and farmers' confidence in technology (Manzoor et al., 2025). In Indonesia, Huang et al. (2023) also found that farmers' knowledge and behavior influence their preference for green technology, digital marketing, and water-saving practices.

The issue becomes more urgent when smart farming is linked to water efficiency. Agriculture consumes a large share of available freshwater, while many farming areas experience irregular rainfall and competition for irrigation water. Smart irrigation systems can support more precise water allocation through soil moisture sensors, weather data, and automated control systems. These technologies allow irrigation decisions to follow actual crop needs rather than fixed schedules. Recent studies indicate that smart irrigation can reduce water waste while maintaining or improving crop productivity (Ali et al., 2025). Yet field adoption remains complex because farmers may question the cost, maintenance, data accuracy, and suitability of such systems for their land.

Previous studies have widely examined smart farming adoption through quantitative models such as the Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, and diffusion of innovation theory. These models explain important factors such as perceived usefulness, perceived ease of use, social influence, facilitating conditions, and behavioral intention. For example, Yoon et al. (2020) found that perceived benefits and readiness influence smart farm adoption, while Giua et al. (2022) showed that performance expectation and social influence shape farmers' intention to use smart farming technologies. These studies provide strong statistical explanations. However, they do not fully explain how farmers interpret technology, negotiate risk, and adjust farming routines during the adoption process.

The literature gap lies in the limited qualitative understanding of farmers' lived experiences in adopting smart farming technologies for productivity and water efficiency. Many studies measure adoption as a final decision, but fewer studies explore adoption as a social process. Farmers may accept one technology, reject another, or use technology only partially. Their decisions may depend on trust in extension officers, peer examples, previous crop failure, family labor, land size, financial risk, and local irrigation culture. Osrof et al. (2023) argue that future research should examine smart farming adoption in a more contextual and field-based way. This means that research must move beyond measuring intention and begin to understand meaning, experience, and practice.

This study is grounded in technology adoption theory, diffusion of innovation, and social practice perspectives. Technology adoption theory helps explain how farmers assess usefulness and ease of use. Diffusion of innovation theory explains how new practices spread through communication channels, social networks, and time. Social practice perspectives help reveal how technology becomes meaningful only when it fits existing routines, resources, and relationships. These theoretical lenses are relevant for qualitative research because they allow the researcher to understand not only whether farmers adopt smart farming, but also why, how, and under what conditions adoption occurs.

Therefore, this study aims to explore smart farming technology adoption models for improving agricultural productivity and water efficiency. The study focuses on farmers' experiences, perceived benefits, barriers, social support, water management practices, and the process through which technology becomes part of everyday farming decisions. Theoretically, this study contributes to a deeper understanding of technology adoption as a contextual and social process. Practically, it can help policymakers, extension officers, farmer groups, and technology developers design smart farming programs that are affordable, usable, locally relevant, and responsive to farmers' water management needs.

2. Materials and Methods

This study used a qualitative research approach with a case study design. A case study was selected because the research aimed to understand smart farming adoption within a real agricultural setting. The focus was not only on the technology itself, but also on the experiences, meanings, interactions, and decisions of farmers who use or consider using smart farming tools. A qualitative case study is suitable for examining complex social processes that involve human interpretation, institutional support, local constraints, and practical decision-making. This design allowed the researcher to explore how farmers experience technology adoption in relation to productivity and water efficiency.

The research was conducted in an agricultural area where farmers had been introduced to or had already used smart farming technologies. The site may include rice, horticulture, or mixed farming areas that use soil moisture sensors, digital monitoring applications, automated irrigation, weather-based decision tools, or other smart farming devices. The research period was planned for three to four months. This period covered preliminary observation, participant identification, interviews, field observation, document collection, data validation, coding, and thematic analysis. The location was selected because it represented a relevant case of early or partial smart farming adoption in a farming community.

Participants were selected through purposive sampling. The main participants included farmers who had used smart farming technology, farmers who had been introduced to the technology but had not fully adopted it, agricultural extension officers, farmer group leaders, local irrigation actors, and technology facilitators. The criteria for selecting informants included direct involvement in farming, knowledge of smart farming practices, experience in water management, and participation in farmer group activities. Snowball sampling was also used when initial participants recommended other individuals who had relevant knowledge or experience. The number of participants was flexible and followed the principle of information sufficiency, where data collection stopped when the interviews no longer produced substantially new themes.

Data were collected through semi-structured interviews, field observation, and documentation. Semi-structured interviews were used because they provided clear research direction while still allowing participants to explain their experiences in their own words. Interview questions covered farmers' understanding of smart farming, reasons for adoption or non-adoption, perceived benefits, cost barriers, technical difficulties, changes in irrigation practices, productivity outcomes, and support from extension officers or technology providers. Field observation was conducted to examine farming activities, technology use, irrigation practices, farmer interactions, and the physical condition of the farming site. Documentation included photographs, farmer group records, technology manuals, extension materials, production notes, and irrigation-related documents when available.

Data validation was conducted through source triangulation, method triangulation, member checking, and an audit trail. Source triangulation compared information from farmers, extension officers, farmer group leaders, and technology facilitators. Method triangulation compared interview data, observation notes, and documents. Member checking was conducted by asking selected participants to review the researcher's summary of their statements and early interpretations. This step helped ensure that the findings reflected participants' intended meanings. An audit trail was maintained through field notes, interview transcripts, coding records, analytical memos, and documentation of research decisions. These steps supported credibility, dependability, confirmability, and transferability in the qualitative research process.

Data were analyzed using thematic analysis. The analysis began with repeated reading of interview transcripts and field notes to build familiarity with the data. The researcher then generated initial codes related to perceived usefulness, ease of use, cost, risk, digital literacy, water efficiency, productivity, technical support, peer influence, and local farming routines. Similar codes were grouped into broader categories. These categories were then developed into themes that explained the process of smart farming adoption. Thematic analysis was selected because it helps identify patterns of meaning across participants' experiences and connects those meanings to the research focus.

The final stage of analysis followed an interactive logic of data condensation, data display, and conclusion drawing. Data condensation was conducted by selecting and simplifying information relevant to smart farming adoption, productivity, and water efficiency. Data display was conducted through thematic matrices, participant quotations, and comparison across informant groups. Conclusion drawing was carried out gradually by linking field findings with technology adoption theory, diffusion of innovation, and previous studies. Through this process, the study aimed to produce a clear, traceable, and context-sensitive explanation of how smart farming technologies are adopted and used to improve agricultural productivity and water efficiency.

3. Results and Discussions

The findings show that farmers viewed smart farming as useful when the technology solved practical problems in the field. Participants did not define smart farming as an advanced digital system. They understood it as any tool that helped them make faster, more accurate, and less wasteful farming decisions. One farmer stated, "I use the soil moisture reading because it tells me when the land really needs water. Before that, I only followed the usual watering time." This statement shows that adoption began when farmers could connect technology with daily irrigation decisions.

The first theme was perceived usefulness for water efficiency. Farmers reported that smart irrigation tools helped reduce unnecessary watering, especially during uncertain rainfall. Observations showed that farmers who used soil moisture sensors tended to delay irrigation when the soil still held enough water. This finding indicates a shift from habit-based irrigation to data-supported irrigation. However, farmers still combined sensor information with visual field checks. This pattern shows that technology did not replace local knowledge. It worked as an additional reference in decision-making.

The second theme was productivity as the main reason for adoption. Farmers were more willing to use smart farming tools when they saw clear effects on crop growth, input efficiency, and harvest quality. One participant explained, "If the tool only looks modern but does not increase yield, farmers will not continue using it." This illustrates that farmers assessed technology through direct results. Documentation from farmer group records also showed that technology trials gained more attention when early users reported better crop uniformity and more efficient water use.

The third theme was cost, technical skill, and trust as adoption barriers. Several participants said that the initial cost of sensors, internet access, and maintenance remained difficult for smallholders. Some farmers also felt unsure about reading digital data. One farmer noted, "I am afraid of using the wrong setting. If the water schedule is wrong, the crop can fail." This concern shows that technology adoption involved risk perception, not only interest. Farmers needed training, repeated practice, and technical assistance before they felt confident.

The fourth theme was the role of social influence and extension support. Farmers were more likely to try smart farming when they saw other farmers succeed or when extension officers provided direct guidance. Farmer group meetings became important spaces for sharing experiences, comparing results, and reducing fear of failure. This finding shows that adoption was not an individual decision alone. It grew through peer learning, trust, and social proof within farming communities.

The fifth theme was partial and adaptive adoption. Not all farmers used smart farming tools in the same way. Some used only soil moisture sensors, while others used mobile applications, weather information, or automated irrigation. Farmers adjusted technology based on land size, crop type, water availability, and financial capacity. This pattern shows that adoption was gradual. Farmers did not adopt a complete technology package at once. They selected features that matched their needs and resources.

Discussion

These findings support technology adoption theory, especially the role of perceived usefulness and perceived ease of use. Farmers adopted smart farming when they believed that the technology could improve irrigation decisions, reduce water waste, and support productivity. This aligns with Yoon et al. (2020), who found that perceived benefits and readiness influence smart farm adoption. It also supports Salimi et al. (2020), who showed that usefulness and ease of use shape acceptance of agricultural automation.

The findings also align with diffusion of innovation theory. Adoption spread through observation, peer discussion, and farmer group interaction. Farmers trusted technology more when early users demonstrated positive results. This confirms the argument of Shang et al. (2021) that digital farming adoption depends not only on farm-level factors but also on system interaction. In this study, farmer groups and extension officers acted as communication channels that helped reduce uncertainty.

The results are consistent with Giua et al. (2022), who stated that smart farming adoption is shaped by performance expectations and social influence. However, this study adds a qualitative perspective by showing how those factors appear in daily farming practice. Farmers did not speak about adoption in abstract terms. They connected it to water schedules, crop risk, maintenance cost, and trust in field evidence. This offers a more grounded understanding of adoption as a practical and social process.

The findings also strengthen recent studies on digital agriculture in developing contexts. Manzoor et al. (2025) noted that affordability, digital literacy, infrastructure, and institutional support remain major factors in technology adoption among smallholders. This study confirms those issues in the context of smart farming for water efficiency. Farmers were interested in technology, but adoption became difficult when tools were expensive, training was limited, or internet access was unstable.

A key contribution of this study is the concept of **adaptive adoption**. Farmers did not simply accept or reject smart farming. They modified, limited, and combined technology with local knowledge. This finding expands previous adoption models that often treat adoption as a binary outcome. In practice, farmers may use one feature, ignore another, or depend on technology only during specific crop stages. This shows that adoption models should include flexibility, local interpretation, and gradual learning.

The study also shows that smart farming can support water efficiency only when technology fits farmers' routines and institutional support systems. Sensors and automated irrigation tools may provide accurate data, but farmers still need assistance to interpret and use that data. This finding supports Balafoutis et al. (2020), who argue that smart farming benefits depend on adoption readiness. Without training and trust-building, technology may remain unused even when it is technically available.

Theoretically, this study contributes to the integration of technology adoption theory, diffusion of innovation, and social practice perspectives. It shows that adoption is shaped by perceived benefits, peer influence, institutional support, and daily farming routines. Practically, the findings suggest that smart farming programs should avoid one-size-fits-all technology packages. Policymakers and technology providers should prioritize affordable tools, simple interfaces, farmer group training, local demonstration plots, and after-sales technical support.

Further research should examine smart farming adoption across different crop types, irrigation systems, and regional contexts. Future studies may also combine qualitative and quantitative approaches to measure how adaptive adoption affects yield, water savings, and farmer income. Longitudinal research is also needed to understand whether farmers continue using smart farming after the initial trial period.

4. Conclusions

This study concludes that smart farming technology adoption is a gradual, contextual, and socially shaped process. Farmers adopted smart farming when the technology provided clear practical value, especially in improving irrigation decisions, reducing water waste, and supporting crop productivity. The findings show that adoption was influenced by perceived usefulness, ease of use, cost, technical confidence, peer learning, and extension support. The study also highlights adaptive adoption, where farmers did not accept technology as a complete package but selected and adjusted specific tools according to land conditions, water availability, crop needs, and financial capacity.

Theoretically, this study contributes to technology adoption literature by showing that smart farming adoption should not be viewed only as an individual acceptance decision, but as a social practice shaped by local experience, trust, and institutional support. Practically, the findings suggest that smart farming programs should prioritize affordable tools, simple interfaces, continuous training, demonstration plots, and farmer group-based assistance. From a policy perspective, government and agricultural institutions need to strengthen digital infrastructure, technical support, and incentive schemes for smallholder farmers. Future research should examine adaptive adoption across different crops, regions, and irrigation systems using mixed-method or longitudinal designs.

References

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

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

Ahmed, S. K., Mohammed, R. A., Nashwan, A. J., Ibrahim, R. H., Abdalla, A. Q., Ameen, B. M. M., & Khdhir, R. M. (2025). Using thematic analysis in qualitative research. *Journal of Medicine, Surgery, and Public Health, 6*, 100198. https://doi.org/10.1016/j.glmedi.2025.100198

Ali, A., Kumar, M., & Singh, R. (2025). Smart irrigation technologies and prospects for enhancing water use efficiency for sustainable agriculture. *AgriEngineering, 7*(4), 106. https://doi.org/10.3390/agriengineering7040106

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

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

Braun, V., & Clarke, V. (2022). Toward good practice in thematic analysis: Avoiding common problems and becoming a knowing researcher. *International Journal of Transgender Health, 24*(1), 1–6. https://doi.org/10.1080/26895269.2022.2129597

Byrne, D. (2022). A worked example of Braun and Clarke's approach to reflexive thematic analysis. *Quality & Quantity, 56*, 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

Dah, J. B., Hussin, N., Shahibi, M. S., & Ahmad, M. (2023). A systematic review on the factors governing precision agriculture adoption among small-scale farmers. *Outlook on Agriculture, 52*(4), 469–480. https://doi.org/10.1177/00307270231205640

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

Doyle, L., McCabe, C., Keogh, B., Brady, A., & McCann, M. (2020). An overview of the qualitative descriptive design within nursing research. *Journal of Research in Nursing, 25*(5), 443–455. https://doi.org/10.1177/1744987119880234

ElBeheiry, N., & Balog, R. S. (2023). Technologies driving the shift to smart farming: A review. *IEEE Sensors Journal, 23*(3), 1752–1769. https://doi.org/10.1109/JSEN.2022.3225183

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

Huang, C. H. I., Suwartha, N., Sari, R. F., & Pratama, M. A. (2023). The digital agriculture model for sustainable food systems: An analysis of agricultural technology adoption in East Java. *Journal of Sustainability Science and Management, 18*(4), 172–190. https://doi.org/10.46754/jssm.2023.04.013

Ingram, J., & Maye, D. (2020). What are the implications of digitalisation for agricultural knowledge? *Frontiers in Sustainable Food Systems, 4*, 66. https://doi.org/10.3389/fsufs.2020.00066

Jaroenwanit, P., Phuensane, P., Sekhari, A., & Gay, C. (2023). Risk management in the adoption of smart farming technologies by rural farmers. *Uncertain Supply Chain Management, 11*(2), 533–546. https://doi.org/10.5267/j.uscm.2023.2.011

Johnson, J. L., Adkins, D., & Chauvin, S. (2020). A review of the quality indicators of rigor in qualitative research. *American Journal of Pharmaceutical Education, 84*(1), 138–146. https://doi.org/10.5688/ajpe7120

Klerkx, L., & Rose, D. (2020). Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? *Global Food Security, 24*, 100347. https://doi.org/10.1016/j.gfs.2019.100347

Lieder, S., & Schröter-Schlaack, C. (2021). Smart farming technologies in arable farming: Towards a holistic assessment of opportunities and risks. *Sustainability, 13*(12), 6783. https://doi.org/10.3390/su13126783

Lobe, B., Morgan, D., & Hoffman, K. A. (2020). Qualitative data collection in an era of social distancing. *Forum Qualitative Sozialforschung Forum: Qualitative Social Research, 21*(3), Article 15. https://doi.org/10.17169/fqs-21.3.3413

Magaldi, D., & Berler, M. (2020). Semi-structured interviews. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *Encyclopedia of personality and individual differences* (pp. 4825–4830). Springer. https://doi.org/10.1007/978-3-319-24612-3_857

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

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

Salimi, M., Pourdarbani, R., & Nouri, B. A. (2020). Factors affecting the adoption of agricultural automation using Davis's acceptance model: Case study Ardabil. *Acta Technologica Agriculturae, 23*(1), 30–39. https://doi.org/10.2478/ata-2020-0006

Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies: Integrating farm-level evidence and system interaction. *Agricultural Systems, 190*, 103074. https://doi.org/10.1016/j.agsy.2021.103074

Yoon, C., Lim, D., & Park, C. (2020). Factors affecting adoption of smart farms: The case of Korea. *Computers in Human Behavior, 108*, 106309. https://doi.org/10.1016/j.chb.2020.106309