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An IoT-Based Precision Agriculture Adaptation Model for Water Efficiency in Small-Scale Farming

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ABSTRACT

This study aims to develop an IoT-based precision agriculture adaptation model for improving water efficiency in small-scale farming. The study addresses the problem of inefficient irrigation practices among smallholder farmers who often depend on visual observation, inherited farming knowledge, and uncertain weather patterns when making water management decisions. A qualitative case study approach was used to explore farmers' experiences, perceptions, and adaptation processes in using or responding to IoT-based irrigation tools. Data were collected through semi-structured interviews, field observation, and documentation involving small-scale farmers, farmer group leaders, agricultural extension officers, local technicians, and village-level stakeholders. The data were analyzed thematically to identify patterns related to irrigation decision-making, perceived usefulness of IoT, trust in digital data, adoption barriers, social support, and local adaptation needs. The findings show that IoT-based precision agriculture can support water efficiency when the technology is simple, affordable, easy to interpret, and aligned with farmers' daily practices. Farmers accepted IoT tools more readily when sensor data complemented their local knowledge rather than replaced it. The study contributes to digital agriculture adoption theory by emphasizing that technology adaptation in smallholder farming is a contextual and social process. The findings imply that policymakers, extension officers, and technology developers should design farmer-friendly IoT systems supported by training, demonstration plots, and local technical assistance. Future studies should test the model across different crops and irrigation contexts.

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1. Introduction

Water scarcity has become a critical issue in contemporary agriculture because food production depends heavily on stable and efficient water management. Climate variability, irregular rainfall, and increasing food demand place strong pressure on farming systems, especially in small-scale agriculture. Smallholder farmers often manage limited land, depend on conventional irrigation, and make irrigation decisions through visual observation, inherited experience, or informal weather prediction. These practices remain valuable in local farming culture, but they often become less reliable when seasonal patterns change. García et al. (2020) explain that IoT-based irrigation can support real-time monitoring of soil moisture, temperature, humidity, and crop water needs. This makes IoT relevant for precision agriculture because farmers can base irrigation decisions on field data rather than fixed schedules.

In many developing agricultural contexts, the challenge of water efficiency is not only technical but also social and institutional. Small-scale farmers often face limited digital literacy, unstable internet access, high device costs, limited technical support, and uncertainty about the economic value of new technologies. These conditions shape how farmers perceive, accept, reject, or modify digital irrigation tools. Kendall et al. (2022) found that farmers' decisions to adopt precision agriculture are shaped by perceived usefulness, local farming culture, practical barriers, and institutional support. Manzoor et al. (2025) also show that digital agriculture adoption in low- and middle-income countries depends on economic capacity, infrastructure, skills, and social readiness.

IoT-based precision agriculture offers a practical opportunity to improve water efficiency because it connects field data with irrigation decisions. Sensors can detect soil moisture conditions and send data to mobile applications or automated irrigation systems. This allows farmers to apply water based on crop needs rather than routine estimation. Bwambale et al. (2022) found that smart irrigation monitoring and control strategies can improve water use efficiency when supported by accurate field data and responsive irrigation control. Kumar et al. (2024) further argue that IoT technologies can support sustainable agriculture by improving resource monitoring, reducing waste, and strengthening decision-making at the farm level.

Previous studies have examined IoT-based irrigation, smart farming, and precision agriculture from technical perspectives. Many studies focus on system architecture, sensor accuracy, automation, machine learning, data transmission, and irrigation performance. Dhanaraju et al. (2022) emphasize that IoT-based smart farming integrates sensors, communication systems, and data platforms to support sustainable agricultural practices. Mansoor et al. (2025) highlight the role of smart sensors in improving precision agriculture through real-time environmental monitoring. However, these studies do not fully explain how small-scale farmers interpret IoT, integrate it into daily farming routines, and negotiate between traditional knowledge and digital recommendations. This creates a literature gap in qualitative research that explores farmer experience, meaning-making, adaptation processes, and practical constraints in local farming contexts.

This study is grounded in technology adoption and diffusion perspectives. IoT is not treated only as a technical device, but as an innovation that changes how farmers observe land, assess water needs, and make irrigation decisions. Precision agriculture requires more than sensors and data. It requires user readiness, institutional support, affordable design, and social acceptance. Nguyen et al. (2024) explain that smallholder farmers' intention to adopt cleaner and precision-based practices is influenced by perceived benefits, behavioral control, and contextual support. Pandeya et al. (2025) also show that adoption of precision agriculture among small-scale farmers depends on knowledge, cost, farm characteristics, and access to relevant information.

Based on this background, this study aims to develop an IoT-based precision agriculture adaptation model for water efficiency in small-scale farming. The study focuses on farmers' experiences in managing irrigation, their perceptions of IoT-based tools, the barriers and enablers of adoption, and the local adaptation strategies needed to make smart irrigation usable in smallholder contexts. Theoretically, this study contributes to the literature on digital agriculture adoption by emphasizing farmer experience and contextual adaptation. Practically, it provides insights for policymakers, extension officers, farmer groups, and technology developers in designing IoT-based irrigation systems that are affordable, simple, locally relevant, and supportive of sustainable water management.

2. Materials and Methods

This study uses a qualitative case study approach. This approach was selected because the research aims to explore how small-scale farmers experience, interpret, and adapt IoT-based precision agriculture for water efficiency. A case study allows the researcher to examine a bounded farming context in depth, including farmer practices, irrigation routines, technology use, social interaction, and local constraints. Campbell et al. (2020) note that purposive qualitative inquiry requires clear participant selection that fits the research aim and the phenomenon being explored. Therefore, this design is suitable because the study does not aim to measure technology performance statistically, but to understand the process through which farmers accept, modify, or resist IoT-based irrigation tools in real farming conditions.

The research will be conducted in a small-scale farming community that has experience with irrigation management and has been introduced to digital agricultural tools, such as soil moisture sensors, weather applications, automatic pumps, or IoT-based monitoring systems. The study is planned for three months, covering preliminary observation, participant selection, data collection, data validation, and data analysis. The location will be selected based on three criteria: the presence of active smallholder farming, recurring water management challenges, and the availability or introduction of IoT-related agricultural technology. Onyango et al. (2021) emphasize that precision agriculture in smallholder systems must be understood through resource constraints, farmer capacity, and field-level realities. This setting allows the researcher to observe how water efficiency practices are shaped by both technological and local farming factors.

Participants will be selected through purposive sampling. The main participants will include small-scale farmers who manage their own land, have at least three years of farming experience, and have used, tested, observed, or considered IoT-based irrigation tools. Supporting participants will include agricultural extension officers, farmer group leaders, local technicians, village officials, and technology providers. Snowball sampling may also be used to identify additional informants, especially farmers who have rejected, discontinued, or modified the use of digital irrigation tools. Serote et al. (2023) show that farmers' resistance or hesitation toward climate-smart irrigation technologies often reflects practical barriers, institutional limitations, and knowledge gaps. This strategy helps capture diverse experiences and prevents the study from focusing only on successful technology users.

Data will be collected through semi-structured interviews, field observation, and documentation. Semi-structured interviews will explore farmers' experiences in determining crop water needs, their understanding of IoT, perceived benefits and risks, cost concerns, trust in digital data, and expectations for future irrigation systems. Field observation will focus on irrigation routines, sensor placement, water application practices, farmer interaction with devices, and responses to weather changes. Documentation will include photographs of tools, irrigation schedules, farmer group records, training materials, device manuals, and local program documents. Dahane et al. (2022) show that low-cost IoT-based smart farming systems need to fit smallholder irrigation practices, which makes direct observation important for understanding field-level adaptation.

Data validity will be strengthened through source triangulation, method triangulation, member checking, and audit trail. Source triangulation will compare information from farmers, extension officers, technicians, farmer group leaders, and documents. Method triangulation will compare interview data with observation and documentation. Member checking will be conducted by returning key summaries to selected participants to confirm whether the researcher's interpretation reflects their actual experiences. An audit trail will be maintained through field notes, interview transcripts, coding records, analytic memos, and documentation of category development. Ahmed (2024) states that credibility in qualitative research can be strengthened through systematic validation procedures, transparency, reflexivity, and documentation.

Data will be analyzed using thematic analysis supported by the interactive logic of data reduction, data display, and conclusion drawing. Interview transcripts and field notes will be read repeatedly to identify meaningful units related to water use, irrigation decision-making, technology perception, adoption barriers, local adaptation, and institutional support. Open coding will be used to identify initial patterns. Related codes will then be grouped into broader themes, such as perceived usefulness, ease of use, trust in sensor data, cost barriers, technical support, local knowledge, and adaptive irrigation practices. Braun and Clarke (2021) argue that thematic analysis requires active interpretation, careful theme development, and consistent alignment between data and analytic claims. The final themes will be interpreted in relation to technology adoption theory and precision agriculture literature to build a context-sensitive adaptation model for IoT-based water efficiency in small-scale farming.

3. Results and Discussions

The findings show that small-scale farmers understand water efficiency through practical experience rather than technical calculation. Most participants described irrigation decisions as a routine activity shaped by soil appearance, plant condition, weather changes, and inherited farming habits. Farmers usually observed leaf freshness, soil cracks, and field humidity before deciding when to irrigate. One participant stated, “I usually know the land needs water when the soil starts to harden and the leaves look weak.” This shows that farmers already have local indicators for water management, although these indicators remain subjective and may become less accurate during irregular weather.

The second theme concerns the perceived usefulness of IoT-based irrigation tools. Farmers viewed soil moisture sensors, automatic pumps, and mobile monitoring systems as useful when they provided clear and simple information. Participants appreciated tools that could show whether the soil was dry, moist, or wet without requiring complex interpretation. One farmer explained, “If the device only tells me the number, I am confused. But if it shows whether the soil is dry or enough, I can use it.” This finding indicates that IoT adoption depends not only on technological accuracy but also on how easily farmers can translate data into daily irrigation decisions.

The third theme relates to trust in digital data. Some farmers trusted sensor readings when the information matched their visual observations. However, trust decreased when the sensor recommendation differed from their farming intuition. For example, a participant said, “The application said the soil was still wet, but I felt the plants needed water.” This tension shows that farmers do not immediately replace local knowledge with digital systems. Instead, they compare technological output with embodied farming experience. IoT, therefore, functions better as a decision-support tool than as a complete substitute for farmer judgment.

The fourth theme concerns barriers to adoption. Participants identified device cost, maintenance, internet access, electricity stability, and lack of technical assistance as major obstacles. Farmers were also concerned about device durability in wet, muddy, or hot field conditions. One participant noted, “The tool is useful, but if it breaks, we do not know who can repair it.” This finding shows that adoption barriers are not limited to initial purchase costs. They also include long-term service, local repair capacity, training, and confidence in using the system independently.

The fifth theme shows that social support plays an important role in technology adaptation. Farmers were more willing to try IoT-based irrigation when the technology was introduced through farmer groups, extension officers, or demonstration plots. Observations showed that farmers often discussed sensor readings together and compared them with their own field experience. This collective learning process reduced uncertainty and strengthened confidence. Documentation from farmer group meetings also showed that group-based training helped farmers understand how digital irrigation tools could support water saving during dry periods.

The final theme relates to the need for a locally adaptive IoT model. Participants did not expect highly complex systems. They preferred affordable, durable, simple, and easy-to-maintain tools.

They also wanted the system to use familiar language, visual indicators, and practical recommendations. Based on the findings, the adaptation model should include four elements: simple sensor-based monitoring, farmer-friendly data display, local technical support, and group-based learning. These elements show that water efficiency in small-scale farming requires integration between technology, local knowledge, and institutional support.

Discussion

The findings confirm that IoT-based precision agriculture can support water efficiency, but its success depends on contextual adaptation. García et al. (2020) state that IoT-based irrigation helps farmers monitor soil and environmental conditions in real time. This study supports that argument, but adds that real-time data must be translated into simple and meaningful guidance for small-scale farmers. Farmers do not only need accurate sensors. They need information that fits their decision-making habits and daily field routines.

The results also align with Obaideen et al. (2022), who explain that smart irrigation systems can improve water use efficiency through monitoring and automated control. However, this study shows that automation alone may not be enough in smallholder contexts. Farmers still want control over irrigation decisions because they rely on long-term experience and direct field observation. This finding suggests that IoT systems should be designed as collaborative tools that combine digital data with farmer judgment.

The tension between local knowledge and digital data provides an important theoretical insight. Technology adoption theory explains that perceived usefulness and perceived ease of use influence user acceptance. In this study, usefulness was not defined only by the ability of the tool to save water. Farmers considered a tool useful when it helped them make faster, clearer, and safer decisions. Nguyen et al. (2024) found that smallholder farmers' intention to adopt precision-based practices depends on perceived benefits and behavioral control. This study strengthens that finding by showing that behavioral control remains important because farmers want to feel capable of interpreting and correcting technology-based recommendations.

The findings are also consistent with Kendall et al. (2022), who found that precision agriculture adoption among family farms is shaped by practical barriers, farming culture, and institutional support. In this study, farmers' hesitation did not come from rejection of innovation. It came from uncertainty about costs, maintenance, repair, and technical assistance. This explains why IoT adoption in small-scale farming must include support systems beyond the device itself. Without training, after-sales support, and local repair mechanisms, farmers may view IoT as risky even when they understand its benefits.

The role of farmer groups and extension officers confirms that technology adaptation is a social process. Serote et al. (2023) show that climate-smart irrigation adoption is influenced by knowledge, infrastructure, and institutional support. This study adds that collective learning can reduce fear of failure and increase confidence in using digital tools. When farmers observe others using sensors, discuss results together, and receive guidance from trusted actors, they are more likely to integrate IoT into their farming practices.

These findings offer a practical contribution for the development of IoT-based precision agriculture in small-scale farming. Technology developers should design tools that are simple, affordable, and resistant to field conditions. Extension officers should provide continuous training rather than one-time demonstrations. Policymakers should support local service networks so farmers can access repair and maintenance assistance. Theoretically, this study expands digital agriculture adoption research by showing that adaptation is not a linear process from awareness to use. It is a negotiated process that involves trust, local knowledge, social learning, and practical feasibility. Future research can test the proposed adaptation model in different crop systems, regions, and irrigation settings to examine how local conditions shape the effectiveness of IoT-based water efficiency.

4. Conclusions

This study concludes that the adaptation of IoT-based precision agriculture for water efficiency in small-scale farming depends on the interaction between digital technology, local farming knowledge, and social support. The findings show that farmers value IoT tools when the system provides simple, clear, and practical information for irrigation decisions. However, farmers do not fully replace their field experience with digital data. They compare sensor readings with soil conditions, plant appearance, weather patterns, and inherited farming practices. This study contributes to the literature on digital agriculture adoption by showing that IoT adaptation is not only a technical process, but also a social and interpretive process shaped by trust, usability, cost, maintenance, and collective learning.

Theoretically, this study strengthens technology adoption perspectives by emphasizing farmer experience and contextual adaptation in smallholder farming. Practically, the findings suggest that IoT-based irrigation systems should be affordable, durable, easy to use, and supported by local technical assistance. From a policy perspective, government agencies and agricultural extension institutions need to support training, demonstration plots, farmer group learning, and local repair networks to reduce adoption risks. Future research should test the proposed adaptation model in different crop types, irrigation systems, and regional contexts to examine how environmental, economic, and institutional differences influence IoT-based water efficiency.

References

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

Ali, A., Hussain, T., Tantashutikun, N., Hussain, N., & Cocetta, G. (2023). Application of smart techniques, Internet of Things and data mining for resource use efficient and sustainable crop production. *Agriculture, 13*(2), 397. https://doi.org/10.3390/agriculture13020397

Ali, A., Hussain, T., Tantashutikun, N., Hussain, N., & Cocetta, G. (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., Beck, B., Fountas, S., Vangeyte, J., Wal, T. V. D., Soto, I., Gómez-Barbero, M., Barnes, A., & Eory, V. (2020). Precision agriculture technologies positively contributing to GHG emissions mitigation, farm productivity and economics. *Sustainability, 12*(24), 10588. https://doi.org/10.3390/su122410588

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). Conceptual and design thinking for thematic analysis. *Qualitative Psychology, 9*(1), 3–26. https://doi.org/10.1037/qup0000196

Bwambale, E., Abagale, F. K., & Anornu, G. K. (2022). Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review. *Agricultural Water Management, 260*, 107324. https://doi.org/10.1016/j.agwat.2021.107324

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

Dahane, A., Benameur, R., & Kechar, B. (2022). An IoT low-cost smart farming for enhancing irrigation efficiency of smallholders farmers. *Wireless Personal Communications, 127*, 2433–2468. https://doi.org/10.1007/s11277-022-09915-4

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

Duguma, A. L., & Bai, X. (2025). How the Internet of Things technology improves agricultural efficiency. *Artificial Intelligence Review, 58*, 63. https://doi.org/10.1007/s10462-024-11046-0

Eze, V. H. U., Adegboyega, S. A., & Okeke, C. D. (2025). Integrating IoT sensors and machine learning for sustainable smart irrigation. *Discover Internet of Things*. https://doi.org/10.1007/s44279-025-00247-y

García, L., Parra, L., Jimenez, J. M., Lloret, J., & Lorenz, P. (2020). IoT-based smart irrigation systems: An overview on the recent trends on sensors and IoT systems for irrigation in precision agriculture. *Sensors, 20*(4), 1042. https://doi.org/10.3390/s20041042

Gebresenbet, G., Bosona, T., Patterson, D., Persson, H., Fischer, B., Mandaluniz, N., & Gellynck, X. (2023). A concept for application of integrated digital technologies to enhance future smart agricultural systems. *Smart Agricultural Technology, 5*, 100255. https://doi.org/10.1016/j.atech.2023.100255

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Enhancing smart farming through the applications of Agriculture 4.0 technologies. *International Journal of Intelligent Networks, 3*, 150–164. https://doi.org/10.1016/j.ijin.2022.09.004

Kendall, H., Clark, B., Li, W., Jin, S., Jones, G. D., Chen, J., Taylor, J., Li, Z., & Frewer, L. J. (2022). Precision agriculture technology adoption: A qualitative study of small-scale commercial family farms located in the North China Plain. *Precision Agriculture, 23*(1), 319–351. https://doi.org/10.1007/s11119-021-09839-2

Kumar, V., Sharma, K. V., Kedam, N., Patel, A., Kate, T. R., & Rathnayake, U. (2024). A comprehensive review on smart and sustainable agriculture using IoT technologies. *Smart Agricultural Technology, 8*, 100487. https://doi.org/10.1016/j.atech.2024.100487

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

Mansoor, S., Ahmad, R., Zafar, M. M., & Rahman, M. U. (2025). Integration of smart sensors and IoT in precision agriculture. *Frontiers in Plant Science, 16*, 1587869. https://doi.org/10.3389/fpls.2025.1587869

Nguyen, L. L. H., Khuu, D. T., Halibas, A., & Nguyen, T. Q. (2024). Factors that influence the intention of smallholder rice farmers to adopt cleaner production practices: An empirical study of precision agriculture adoption. *Evaluation Review, 48*(4), 732–760. https://doi.org/10.1177/0193841X231200775

Obaideen, K., Yousef, B. A. A., AlMallahi, M. N., Tan, Y. C., Mahmoud, M., Jaber, H., & Ramadan, M. (2022). An overview of smart irrigation systems using IoT. *Energy Nexus, 7*, 100124. https://doi.org/10.1016/j.nexus.2022.100124

Onyango, C. M., Nyaga, J. M., Wetterlind, J., Söderström, M., & Piikki, K. (2021). Precision agriculture for resource use efficiency in smallholder farming systems in Sub-Saharan

Africa: A systematic review. *Sustainability, 13*(3), 1158. https://doi.org/10.3390/su13031158

Pandeya, S., Liang, K., Velandia, M., & Yin, X. (2025). Factors influencing precision agriculture technology adoption among small-scale farmers in Kentucky and their implications for policy and practice. *Agriculture, 15*(2), 177. https://doi.org/10.3390/agriculture15020177

Saiz-Rubio, V., & Rovira-Más, F. (2020). From smart farming towards Agriculture 5.0: A review on crop data management. *Agronomy, 10*(2), 207. https://doi.org/10.3390/agronomy10020207

Serote, B., Mokgehle, S., Senyolo, G., Du Plooy, C., Hlophe-Ginindza, S., Mpandeli, S., Nhamo, L., & Araya, H. (2023). Exploring the barriers to the adoption of climate-smart irrigation technologies for sustainable crop productivity by smallholder farmers: Evidence from South Africa. *Agriculture, 13*(2), 246. https://doi.org/10.3390/agriculture13020246