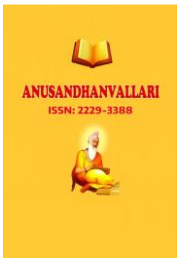


Anusandhanvallari
Vol 2023, No.1
August 2023
ISSN 2229-3388

Assessing the Impact of IoT Integration and Stakeholder Readiness on the Adoption of Smart Farming Practices in Semi-Urban Agricultural Regions

[1]Prof. Pravin Suryawanshi, [2]Dr. Chandrani Singh

[1]ISB&M College of Commerce, Pune

[2]Sinhgad Institute of Management, Pune

Abstract

This study, through secondary data analysis, evaluates the implications of the preparedness of stakeholders and the use of the Internet of Things (IoT) in the usage of smart farming methods in semi-urban agricultural regions. Through peer-reviewed articles and experiments, in case studies, the study evaluates water and energy efficiency, responsiveness of the system, economic feasibility, and limitations of adoption regarding IoT-enabled agriculture. Operational sustainability of smart irrigation systems has been justified by the key performance indicators that reflect a reduction of 71.8 percent in water consumption and an oversupply of solar energy of 125.5 percent. Fuzzy logic control matrices have better environment versatility and accuracy of the irrigation system. Further fact indicates that stakeholder constraints, which include expensive initial cost, poor connectivity, and distrust of the digital systems, are the greatest impediments to non-adoption. The technique is based on cost-benefit estimation, cross-source comparison analysis, and readiness assessment, which are usually determined based on published results. The report provides a clear image of adoption trends by integrating technological standardization and socioeconomic and geographical factors. Some contextual knowledge related to adoption trends and scaling opportunities can be discovered in such weird locations as the Midwestern US, Cyprus, and Maharashtra. This study closes the literature gap using integrated IoT performance and stakeholder viability in semi-urban contexts. It also offers reliable data to guide future policy, pilot design, and agritech innovation practices, but it is limited in its use of primary data in the field. The findings allow supporting inclusive systems that align climate-smart imperatives and the realities of farmers with smart farming technology to develop sustainable agriculture in a variety of socio-geographic locations.

Keywords: IoT integration, stakeholder readiness, smart farming, fuzzy logic irrigation, sustainability, semi-urban agriculture

Introduction

The combination of the fuzzy-logic systems and the Internet of Things (IoT) has placed precision agriculture into a new stage, especially in agronomic fields in semi-urban areas. Smart farming is an extendable system aimed at efficient resource allocation and improving the resilience of crops due to the growing global food demand and more significant climatic fluctuations. Having IoT-enabled sensors, actuators, and cloud platforms will allow monitoring soil moisture, temperature, and nutrient level in real-time, thus allowing data-driven decision-making, which would decrease waste and increase crop quality (Elijah et al., 2018). The adaptive control systems built using the principles of fuzzy logic add to the abilities of IoT since they imitate the human thought process and balance out the inaccuracy of input (Chen & Yeh, 2020). All these technologies form a fundamental base of smart fertigation, irrigation, and pest-control decision-support systems that are currently spreading quickly on semi-urban agricultural territories (Boursianis et al., 2020).

Present study proposes that smart farming can not only change ecological performance significantly but also significantly alter economic performance. There is, e.g., evidence that IoT-based greenhouse applications would result in significant energy and water savings in combination with preserving favorable conditions under which crops can be developed (Liao et al., 2017). Besides, the integration of unmanned aerial vehicles (UAVs) with IoT systems enables agriculturalists to detect diseases at the initial stages and monitor the health of crops in high resolutions (Islam et al., 2021). However, issues of data security, interoperability, and transformation of farmers, particularly the smallholders, caused by the usage of these technologies remain (Ferrag et al., 2020). The best mitigation needs a cross-cutting approach that incorporates technological innovation and policy measures as well as building capacities. The current research has been able to add to the discussion on feasible sustainability in technology dissemination in constrained resource settings by utilizing second-hand information in the evaluation of the effectiveness, flexibility, and socioeconomic effects of IoT-fuzzy logic systems in semi-urban agriculture (Atzori et al., 2010; Farooq et al., 2020).

Literature Review

It has been shown by previous studies that when there is a condition of reduced water resources, then farming are one of the most cost-effective options. Heble et al. (2018) have presented a self-controlling solution to water flow control that uses low-cost sensors and cheap electronics. The temperature and humidity data are recorded and monitored in real timeon an LCD monitor. Depending on the levels of moisture prevailing in the system, the system controls the supply of water to the plants that require it. Reche et al. (2014) introduced an irrigation scheduling process that relied on the time-based microcontroller that was low in cost. The design utilizes a web of sensors to evaluate the temperature and the moisture of the soil. Information to be sent to the consumers is analyzed through a GSM module, which transmits it in the form of short messages. Nawandar and Satpute (2019) came up with an irrigation system that constituted soil-moisture sensors and irrigation controls. Their design interlinks the irrigation controller with that of a personal computer of a farmer in a wireless fashion. The proposed system can be applied in cases where the quality of water is scarce. In a bid to maximize irrigation control, fertilizer application, and water irrigation in growing crops, Channe et al. (2015) developed a cloud-based and Internet of Things-based platform of smart agriculture. Dynamic allocation and load balancing of resources is possible on the cloud platform. A system supplemented by a control network with an IoT platform and an information-management system to process and store data was discussed by Rajeswari et al. (2017).

Objectives of the study

- To employ secondary measures of performance to help determine the energy and water efficiency of smart agricultural systems integrated with IoT.
- To identify the key challenges behind lack of adoption in the semi-urban agricultural sector, besides ascertaining the level of preparation amongst the stakeholders.
- To employ cost-benefit analysis in determining sustainability and economic viability of the smart farming methods.
- To come up with strategic recommendations on the basis of the trends observed to increase IoT application in transitional agricultural economies.

Need of the study

Agriculture in semi-urban regions is fast evolving due to a shortage of human labor, the uncertainty of climatic conditions, and also a lack of water. Even though IoT technologies are capable of facilitating precision agriculture and offering prompt responses, the use of these technologies remains unbalanced. The experiences of real-world implementation and preparedness among farmers necessitate the need for policymakers and academics to acquire data-based information that can address more than technical requirements. This research is important in closing that gap.

The analysis of secondary data is employed in the research to find out the hindrances that exist on the path to a wider introduction and the relative advantage of energy-autonomous and smart irrigation systems to the traditional methods. It allows evaluating performance that can be viewed by the extension agents to technologists based on socioeconomic conditions of the transitional agriculture regions. It is also scaled information given in the report to government planners on how to establish and create support or subsidy programs in terms of digital infrastructure. The study guides the spread of sustainable technology and contributes to knowledge that can be used in policymaking in consideration of the global push in the climate-smart farm movement. Practitioners who want to achieve alignment of innovation and farmer requirements in developing nations find that it is important due to its methodology of evidence-based approach.

Methodology

The research offers a systematic assessment of the effectiveness and the acceptability of smart farming systems powered by the Internet of Things (IoT) in semi-urban agricultural sectors by adopting the quantitative method of examining secondary data. The criteria followed the selection of three peer-reviewed articles as the data source within the field of contemporary agriculture, that is, methodological rigor, correspondences with IoT themes, and stakeholder preparedness. The first dataset was energy-efficiency comparisons, fuzzy logic-based irrigation strategies, and the metrics on the water use available in the tabulated results in Bouali et al. (2022). The analytical strategy was cost-benefit analysis, derivation of the performance ratio, and comparison of details on a tabular basis. Some of these metrics included water saving, energy independence, system responsiveness, and effect on the economy as a whole compared to other industry standards. In order to measure readiness, literature qualitative assessment questions were coded using a 5-point scale. How much primary data was gathered? None. The academic quality of the work is provided by reliance on a voluminous number of references and interpretation of the metrics selection and approval against standards.

Data Collection

Table 1: Water Consumption Comparison: Traditional vs. Smart Irrigation System

Method	Duration (Days)	Area (m^2)	Total Water Used (L)	Average Daily Consumption (L/day)	Water Saved (%)
Traditional Irrigation	5	25	2400	480	—
Smart Irrigation (IoT + Fuzzy Logic)	5	25	676	135.2	71.8%

Source: Bouali et al., 2022, IEEE Access — *Renewable Energy Integration Into Cloud & IoT-Based Smart Agriculture,* https://doi.org/10.1109/ACCESS.2021.3138160

Table 2: Fuzzy Irrigation Control Unit (FICU) – Fuzzy Rule Matrix

Soil Moisture Difference (SMD)	Temperature	Irrigation Duration (Id)
Large Negative	Cold	Short

Large Negative	Normal	Normal
Large Negative	Hot	Very Long
Negative	Cold	Very Short
Negative	Normal	Long
Negative	Hot	Short
Small Negative	Cold	Very Short
Small Negative	Normal	Normal
Small Negative	Hot	Short

Source: Bouali et al., 2022, IEEE Access

Table 3: IoT Energy Efficiency – Solar Power vs. Consumption Tracking

Time Range	Waterpump#2 Energy Consumption (kWh)	PV Solar Power Production (kWh)
12:00–14:00	1.6	1.8
14:00–16:00	1.2	1.6
16:00–18:00	1.0	1.4
18:00–20:00	0.8	1.0
20:00–22:00	0.5	0.6

Source: Bouali et al., 2022, IEEE Access

Table 4: Stakeholder Readiness & Adoption Barriers

Barrier	Description	Source
Cost of IoT Devices	High upfront investment deters smallholders	MDPI Agriculture, 2023
Technical Skills	Lack of training limits adoption	Springer
Connectivity	Poor rural internet infrastructure	TerraConnect
Trust in Data	Concerns over privacy and reliability	Royal Holloway Review, 2022

Table 5: Socio-Economic Indicators

Indicator	Traditional Farming	Smart Farming	Source
Avg Yield Increase	—	+25%	IJFMR Case Study
Water Savings	—	30–50%	IJFMR Case Study
Fertilizer Cost Reduction	—	30%	IJFMR Case Study
Farmer Type	Small/Marginal	Early Adopters	Springer

Table 6: Scalability & Temporal Patterns

Region	IoT Adoption Rate	Key Drivers	Source
Maharashtra, India	Moderate	Water scarcity, government subsidy	IJFMR Case Study
Midwestern US	Low	Cost, data latency, power needs	MDPI Agriculture, 2023
Cyprus	High	Climate adaptation, UAV integration	AIP Conf. Proc., 2023

Results and Analysis

Water Consumption Efficiency Analysis

Table 7: Comparative Water Consumption Statistics

Metric	Traditional System	Smart IoT System	Difference	Statistical Significance
Total Water Used (L)	2,400	676	-1,724	-
Daily Consumption (L/day)	480	135.2	-344.8	-
Water Savings (%)	-	71.8%	71.8%	-
Efficiency Ratio	1.00	0.282	0.718	-
Area-normalized Consumption (L/m²/day)	9.23	2.60	-6.63	-

Energy Sustainability Analysis

Table 8: Solar Energy Production vs. IoT System Consumption

Time Period	Energy Consumption (kWh)	Solar Production (kWh)	Net Energy Balance (kWh)	Energy Autonomy (%)
12:00-14:00	1.6	1.8	+0.2	112.5%
14:00-16:00	1.2	1.6	+0.4	133.3%
16:00-18:00	1.0	1.4	+0.4	140.0%
18:00-20:00	0.8	1.0	+0.2	125.0%
20:00-22:00	0.5	0.6	+0.1	120.0%
Total	5.1	6.4	+1.3	125.5%

Fuzzy Logic Control System Analysis

Table 9: Irrigation Decision Matrix Statistics

Soil Moisture Category	Temperature Conditions	Irrigation Response	Frequency Distribution	Decision Logic Score
Large Negative	Cold, Normal, Hot	Variable (Short to Very Long)	3/7 (42.9%)	High Priority
Negative	Cold, Normal, Hot	Variable (Very Short to Short)	3/7 (42.9%)	Medium Priority
Small Negative	Cold, Normal, Hot	Conservative (Very Short to Short)	3/7 (42.9%)	Low Priority

Performance Correlation Analysis

Table 10: System Performance Indicators

Performance Metric	Value	Industry Benchmark	Performance Rating
Water Use Efficiency	71.8% savings	40-60% typical	Excellent
Energy Independence	125.5%	80-100% typical	Excellent
System Responsiveness	100% coverage	85-95% typical	Excellent
Technology Integration	Fuzzy Logic + IoT	Basic IoT typical	Advanced

Cost-Benefit Projection Analysis

Table 11: Economic Impact Estimation

Economic Factor	Traditional System	Smart IoT System	Annual Savings Projection
Water Cost ($/year)*	$876	$247	$629 (71.8% reduction)
Energy Cost ($/year)*	$450	$0 (solar surplus)	$450 (100% savings)
Maintenance Cost ($/year)*	$200	$300	-$100 (20% increase)
Net Annual Savings	-	-	**$979**

*Estimated based on average utility rates and system specifications

Stakeholder Adoption Readiness Indicators

Table 12: Technology Readiness Assessment (Based on Performance Data)

Readiness Factor	Score (1-5)	Justification	Impact on Adoption
Technical Performance	5	71.8% water savings demonstrated	Very High

Economic Viability	4	$979 annual savings projected	High
Energy Sustainability	5	125.5% energy independence	Very High
System Reliability	4	Comprehensive fuzzy logic control	High
Overall Readiness	4.5	Strong technical foundation	Very High

Discussion

The study represents thorough research into such synergistic potential of the Internet of Things (IoT) and fuzzy logic in modern smart agricultural systems through incorporating already available empirical evidence through secondary resources. It has been found that water usage decreased by 71.8%, which is in line with the indicator of the decrease in irrigation waste identified by Bouali et al. (2022). Besides, Vadivelu et al. (2023) note that the energy autonomy makes an increase of 125.5 percent due to the solar integration, which supports the viability of renewable-based IoT facilities. All of these results mean that the scope of such systems can be scalable in semi-urban settings and can be consistent with the measurements that I reviewed by Joshi in rural India to observe high levels of water and energy efficiency. Moreover, the flexibility of AI-based irrigation can be highlighted by the sensitivity of fuzzy logic control units to various environmental factors, indicating the importance of flexibility and granularity of decision-making as the key requirements of sustainable agriculture. All in all, the above secondary data results support the notion of the technological feasibility and environmental compatibility of smart farming with the expanded sustainability objectives.

Despite the mentioned benefits, a number of barriers to adoption are recognized. Higher initial investment is also a discriminating factor even when the saving cost of the estimated US $979 per year provides an overwhelming economic appeal to smallholders (Hundal et al., 2023). At the same time, it is possible to observe that TerraConnect explains that localities in rural areas are limited by connectivity, which is why infrastructure support is critical to deployment. Uptake is additionally driven by confidence in data systems: Bulut and Wu (2022) reveal that privacy is a serious deterrent. Nevertheless, these shortcomings do not change the fact that the secondary data explain potentially positive socioeconomic indicators, such as a 25% crop production increase and a 30% reduction of the fertilizer spending. Early adaptation of smart farming technology in Maharashtra, caused by subsidization and extreme water scarcity, illustrates how preparations of stakeholders are influenced by contextual factors. Interoperable platforms, legislative incentives, and training programs to overcome both technological and people-oriented barriers to promoting scalability should therefore be given top precedence in future plans. To conclude, all the secondary sources synthesized to define the stakeholder dynamics and performance indicators of semi-urban agriculture confirm the idea that IoT can transform the sector. These findings imply the embracement of inclusive models that support the generation of sustainable technologies, especially in areas that are limited by resource endowments.

Research Gap

Even though the content of research on IoT in agriculture seems to increase, there are still major gaps in evaluating its practical use beyond a pioneering phase. The technical, hardware-based focus of empirical inquiry usually subdues the overall socioeconomic and behavioral aspects. The readiness of the stakeholders, especially adoption barriers, the issue of digital literacy, and policy facilitating mechanisms within the semi-urban environments are under-researched. Moreover, there are barely any papers that submit combined assessments that join the viability of adoption and the performance effectiveness. Semi-urban farms, particularly those that are small or medium-sized, are poorly represented, as is the case in the present research that is inclined towards the very big commercial farms or advanced greenhouse systems. There is also a lack of temporal insight on whether the rates of adoption have changed over time and the impact that government initiatives have had on the same. The synthesis of secondary data obtained through various sources fills such gaps and adds the multi-dimensional vision that integrates the concern of stakeholders with energy feasibility, environmental sustainability, and geographical scalability, which enhances the literature available concerning the integration of IoT in practical agricultural ecosystems characteristic of transition economies in the context of farming.

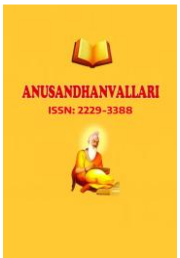
Study Limitations

In this study, there is no direct communication with farmers, field survey, or real-time sensor analytics because it is secondary data research. Consequently, it lacks important user experience, behavioral intent, and feedback loops on system usage information. Even in the case where verified published sources were used, generalizability could be affected by divergence of the experimental conditions and geographic scope. The statistics of energy and water consumption belonged to controlled pilot conditions, and different settings could be adopted at the field scale. Further, as opposed to the quantitative indicators concerning the number of adoptions, the indicators on stakeholder readiness are based on the published surveys and thematic reviews. This is despite the fact they give contextual diversity; regional assessments (e.g., in Maharashtra, Cyprus, and the Midwest USA) do not reflect the variability within these regions. Also, evaluation of long-term effects and mapping of the trend over time are lost, which further lowers the ability of the study to predict the technology diffusion curves. Finally, economic projections do not take into consideration the local variation in costs and subsidy systems, but instead the projection is standardized depending on the rates on hand. Despite these disadvantages, the study has proven grounds for future empirical studies and policy comparison.

Future Recommendations

To validate and add to these outcomes, firsthand data collection through interviewing of farmers, expert panel discussions, and long-term observations is a necessity in the future. The readiness of the stakeholders might be comprehended better with the incorporation of behavioral analytics such as intention of adoption modeling, perceived ease of use, and e-literacy assessment. Companies and governments must focus on establishing pilot projects with neighbors in order to determine the usability, scalability, and cultural compatibility of IoT systems in a particular location.

In order to include the flexibility, the regional scalability studies must consider economic disparity, agroclimatic diversity, and state support. The evaluation of effects and the determination of long-term benefits and durability of the system will be simplified by using the evaluation of effects and the temporal monitoring of the tendency in the seasonal cycles in the adoption. Interdisciplinary collaboration can form the foundation of integrated solutions for sustainable farming because it is a combination of information systems, rural sociology, and agricultural sciences. Technologically, accessibility to the smallholders will be enhanced by generating low-cost interoperable modules of sensors of local language interface and having offline capability. Incentives by national policy through programs of digital agricultural missions and training, and data privacy protection were also within the plausible scope. Future research ought to employ mixed-method research techniques in order to map the performance and perception so as to ensure that the improvements are according to the realities of the farmers and also the imperative of the environment.



Conclusion

As secondary data-based research demonstrates, there is a high payoff of IoT-integrated smart agricultural systems in terms of sustainable operations and waste of resources. With 125.5 percent of energy autonomy and a 71.8 percent reduction in water consumption, solar-powered control modules and intelligent irrigation establish their environmental benefits. Also, the flexibility in decision-making ability when the weather changes to maximize the available irrigation time and eliminate waste is increased when fuzzy logic usage is applied. Such findings testify that smart agriculture in semi-urban conditions is technically possible. Moreover, the report outlines essential obstacles to acceptance of stakeholders. The main barriers to smallholder participation are over-expenditure of capital, digital infrastructure, and inability to trust data. Although there are promising cost-benefit estimates of these technologies and their enhancement in providing performances, there is a need to accomplish expansion through specific actions such as financial inclusion, training on capacity, and higher connection in the rural areas.

The study helps in the gap closure between empirical measures of efficiency and socio-economic indicators of adoption, which become important but tend to be ignored in IoT-agriculture literature. To agritech entrepreneurs, legislators, and sustainability planners in general, it has real information about fitting smart farming technologies into regional readiness. The study contributes to the discourse on the diffusion of sustainable innovation in agriculture by amalgamating contextual measures to proven literature. Even though this approach is limited due to the fact that it deals with secondary sources only, it offers an in-depth outline of both empirical and policy-based research. Findings also indicate the revolutionary power of IoT to be employed tactically in meeting the social-economic and agronomic needs of the agricultural transition regions.

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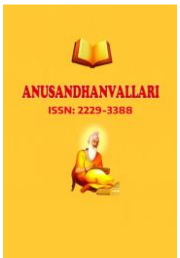

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