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Transforming Agriculture in South AlBatinah (Oman): IoT-Enabled vs. Traditional Greenhouses and Their Impact on Self-Sufficiency

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ABSTRACT

Background: Transforming agriculture is essential for achieving sustainability and food security in Oman. This research presents a comparative analysis of traditional and IoT-based greenhouse farming in South Al Batinah, focusing on four objectives: (1) analyze the relationship between IoT usage and adoption levels; (2) determine the barriers preventing adoption by traditional farmers; (3) assess the socio-economic, environmental and social impacts of IoT versus traditional practices and (4) evaluate the level of government support and future needs.

Methods: The study surveyed 25 greenhouse farmers in Barka, Suwaiq and Al Mussanah using a structured questionnaire Data analysis employed chi-square tests of independence and goodness-of-fit, Mann-Whitney U tests and descriptive ranking.

Result: Mann-Whitney U test results show that IoT adopters achieve higher productivity, better produce quality, lower costs and improved resource-use efficiency than non-adopters, while income differences remain statistically insignificant. Adoption barriers are mainly financial and knowledge-based, with high initial investment (89.5%) and lack of incentives (84.2%) most frequently reported. Most greenhouse owners also highlighted weak government regulation of imported fruits and vegetables, which depresses local prices and price-based competition from traditionally produced-often lower-quality-produce. This price-driven market environment reduces the economic viability of IoT adoption. Overall, IoT-enabled greenhouse farming enhances efficiency and sustainability, but wider adoption depends on supportive policies for pricing regulation, finance, training and market facilitation.

Key words: Adoption barriers, Economic impacts, IoT greenhouses, Sustainability.

INTRODUCTION

The agriculture sector in the Oman is one of the significant components in ensuring a stable and secure food policy for the nation. This significance is even more pronounced due to the stringent arid conditions prevailing in the country, the difficulty in the availability of agricultural land and the scarcity of water. Traditional greenhouse systems that have been practiced in Oman have structurally allowed for the effective management of climatic conditions, providing protective environments for plant growth and control pollution. (Al-Mezeini *et al*., 2020; Narmilan *et al*., 2020) found that Greenhouse production in Oman is inefficient, with excessive water and electricity consumption and ground water salinity. He also found that 79% of greenhouse farmers in Oman are technically inefficient, with average efficiency scores of 73% and water and electricity consumption exceeding optimal levels by 54% and 46% respectively. IoT greenhouses use sensors, actuators and microcontrollers to track environmental variables including temperature, humidity, soil moisture, nutrient levels and light intensity (Lanitha *et al*., 2022; Tripathy *et al*., 2021). In this regard, IoT greenhouse systems coordinate automatic, data-driven, more precise controls including earlier detection of plant stress, pest or disease outbreaks, or equipment failure, thereby regulating the internal space and growing conditions (Subahi and Bouazza, 2020; Rayhana *et al*., 2020; Simó *et al*., 2023; Kerkhof *et al*., 2021). For example, IoT systems are able to correlate soil moisture readings and weather data to better schedule irrigation (Tawfeek *et al*., 2022; Hussein *et al*., 2024; Lal *et al*., 2020).

When data from sensors (Huynh *et al*., 2023), actuators and prescriptive analytics are manifested and accessible, the IoT system can measure these factors and continuously control and adjust them to retain an ideal scenario based on the type of crops (*e.g*., temperature, humidity and light

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exposure). Such accuracy supports the sustainable growth of plants and high crop yield. Research also demonstrates that IoT based irrigation device and nutrient delivery is ensuring that the crop is accurately grown during the stages of its life cycle and subsequently impact productivity and quality of the crop (Rizwan *et al*., 2023; Oduwole *et al*., 2020). The use of IoT systems also ensures that actions to contain outbreaks of disease and pest control can be timely and accurate (Huynh *et al*., 2023) as it reduces the human error and thus allows the standardization of the agricultural practices (Jayashankar *et al*., 2018). But network unavailability, internet device usage, IoT-trained farmers, familiarity of the farmers with the devices, are found to be the prominent hindrances that discourage farmers from acquiring IoT devices for production (Lanitha *et al*., 2022). Research also indicates that IoT applications enhance the efficiencies of water and energy that are inherently central to Oman: environmental control and smart irrigation (Jin *et al*., 2020; Lanitha *et al*., 2022). Smart management of energy to balance or maximize crop environments and conserve the overall energy could also be achieved through IoT (Tominaga *et al*., 2024; Pandey *et al*., 2023). Such safe adapter greenhouse technologies reduce dependence on chemical fertilizers and pesticides and therefore stimulate environmental sustainability) (Rizwan *et al*., 2023; Shanto *et al*., 2023). It would be beneficial in the Omani case because it will be contributing to the plans of sustainable development and stimulating environmental protection. Farmers will swap “overproduction” with acting-informed and social tracked rather than clueless with the help of the IoT-based systems. Whereby gain skill and creation of innovative technologies (Jepkorir *et al*., 2022). It is also the Local community contribution to transformation from the conventional to the IoT based agricultural approach (Hazmi *et al*., 2023). IoT-aided solutions are capable of integrating energy efficiency in order to decrease the consumption of the energy while enabling growth condition optimization (Bersani *et al*., 2021; Gong *et al*., 2023). Predictive control and automation has also been proposed that it could lead to near zero powered greenhouses (Bersani *et al*., 2021). Therefore, renewable energy strategies such as the rain-driven nanogenerators could be sustainable power sources of the agricultural locations that are off-grid (Zhang *et al*., 2021). However, according to the views of farmers in Oman, installation costs, internet infrastructure weakness and farmers’ technical literacy are barriers against adoption of intelligent farming techniques (Lianying *et al*., 2024; Naidu *et al*., 2020). The connectivity and training at policy level and support necessary of farmers are circumstances that should ease the barriers (Lianying *et al*., 2024). The application of IoT systems can revolutionize agricultural procedures through better-timed irrigation control using live information from moisture meters in the soil and meteorological data. which is highly critical in Oman’s water-scarce environment? (Tawfeek *et al*., 2022; Lanitha *et al*., 2022). The comparison between IoT approaches and traditional greenhouses in Oman illustrates the friction between erstwhile practices and a movement towards adopting technological advances and raises key concern in financial affordability, investment and farmers being ready for change. IoT systems are comprised of initial implementation costs, however they are sustainable, affordable and scalable for different levels of farmers (Jayashankar *et al*., 2018, Alsayaydeh *et al*., 2023; Jitea *et al*., 2021). Other parts of the world has been able to proof that IoT technologies can increase productivity and can also promote relatively more sustainable resource use, while also providing climate resilience improvement the which is necessary for an advancement of agriculture in Oman (Velten *et al*., 2015; Chami *et al*., 2020). This study aims to compare traditional and IoT-based greenhouse farming in Oman in order to determine the extent of IoT adoption in greenhouse farming and identify the barriers preventing farmers from adopting IoT in their operations. It further seeks to examine the environmental, social and economic impacts of IoT-enabled greenhouse farming in the local context.

Objectives and hypothesis of the study

1. To examine the association between farmers’ adoption status of IoT-based greenhouse farming solutions and the types of IoT technologies they utilize.
2. To identify and rank the barriers that discourage traditional farmers from adopting IoT-enabled greenhouse farming.
3. To critically evaluate the impact (economic, environmental and social) of adopting IoT-enabled greenhouse technologies compared to traditional greenhouse practices.

Hypothesis 3.1 (H_{01}): There is no significant difference in economic impacts between IoT adopters and non-adopters in greenhouse farming.

Hypothesis 3.2 (H_{02}): There is no significant difference in environmental impacts between IoT adopters and non-adopters in greenhouse farming.

Hypothesis 3.3 (H_{03}): There is no significant difference in social impacts between IoT adopters and non-adopters in greenhouse farming.

MATERIALS AND METHODS

The study involved a quantitative, cross-sectional design, which aimed to assess the extent of Internet of Things (IoT) technology in greenhouse agriculture of Al Batinah region, Oman, with a special focus on the wilayats of Barka, Suwaqi and Al Mussanah. These areas are the hub of the green house in Oman, with the most traditional kinds of greenhouses but also with a significant number of IoT-based greenhouse operations, thus they provide a good ground for comparison. A comprehensive questionnaire was used to collect data from the Farm houses. Questions on demographic characteristics, adoption status, type of IoT technology, technology adoption obstacles as well as the description of economic, environmental and social implications were included in the questionnaire. The study employed purposive sampling to identify greenhouse farms

in Barka, Suwaqi and Al Mussanah, in the Al Batinah region, due to their high density of both traditional and IoT-enabled green houses. The farms were selected using the agricultural offices, extension services and field visits and only actively running greenhouses were considered. The sample consisted of the adopters of IoT (n = 7) and non-adopters or those who are at the initial stages of adopting the technologies, as there is a lack of diffusion of IoT technologies in Omani greenhouse agriculture. The sample size was sufficient to conduct a non-parametric analysis and to predict the main patterns of adoption and limitations because of the exploratory nature of the research, the situation of early adoptions and the data type (ordinal). Further, the sample was divided into two groups, Group 1 consisted of farmers who were involved in the use of IoT-based greenhouse technologies (n=7), while Group 2 of farmers who had not yet adopted or were at the initial stage. Due to a relatively small sample size and the nature of the data which were mostly measured using ordinal scales the use of non-parametric statistical methods was considered. In order to fulfill the first research objective, the relationship between farmers' adoption status and the specific types of IoT technologies implemented was assessed through the Chi-square test of independence. The Chi-square test is particularly adept at exploring relationships among categorical variables and is extensively utilized within studies focusing on agricultural innovation and technology uptake (Agresti, 1996; Bewick *et al*., 2004). For addressing the second objective, understanding the hindrance for IOT adoption ranking method is used as per their responses based on their frequency and percentage representation. This methodology aligns with previous adoption research which prioritizes constraints to underscore their comparative significance for policy interventions (Rogers, 2003). The Mann-Whitney U test was used to evaluate the economic, environmental and social impacts of adopting IoT technology, as it's particularly effective for small, non-parametric, ordinal data (Mann and Whitney, 1947; Nachar, 2008). Two independent groups were compared at a significance level of 5%. A p-value of less than 0.05 indicated that there were significant differences between the two groups. Descriptive statistics provided an overview of the support needs, while qualitative analysis highlighted policy recommendations.

Findings and analysis

Demographic profile

The survey covered 25 greenhouse farmers, with 7 using IoT systems and the rest traditional. Most respondents (76%) were aged 31-60, while 48% had no schooling and only 16% had secondary education. Roles were mainly operational: 68% farmers/supervisors and 32% owners. In terms of adoption, 48% used traditional, 40% hybrid and only 12% IoT-based systems. Major crops included leafy greens (52%), tomatoes (44%), peppers (40%), with some diversification into avocado, capsicum, pears and flowers.

Analysis of objective-1

Above Table 1, the study shows that the use of Automated Irrigation Systems and Temperature and Humidity Control Sensors was very strongly related (χ^2= 10.29, p = 0.0013). This means that the use of these tools is very widespread and is also statistically significant among the IoT users. In the same way, AI-Based Crop Monitoring had a statistically significant correlation (χ^2 = 4.57, p = 0.0325), which indicates that it can continue to be an important technology among the group even if the users who adopted it were less. Additionally, Smart Pest Control Systems, Cloud-Based Farm Management Platforms actually didn't were insignificant as per their respective p-values (χ^2 = 10.29, p = 0.13). In contrast, the soil moisture sensors (χ^2 = 1.14, p = 0.2850) and the remote control *via* Mobile Applications (χ^2 = 1.14, p = 0.2850) did not exhibit statistically significant relationships as their p-values were more than the threshold of 0.05. The general result from the findings reveals the fact that there is a very tight connection of core systems of the greenhouse like automated irrigation and environmental monitoring, over another advanced feature, for example, pest control and cloud management, soil moisture sensor and mobile application.

Analysis of objective-2

The high initial investment expenses (89.5%), which include purchasing, setup, maintenance and integration, are the main reason why farmers are reluctant to adopt IoT technology, as Table 2 illustrates adoption is impossible due to a lack of financial incentives or support, as reported by 84.2% of respondents.73.7% of respondents reported resistance to departing from customs, which reflected

Table 1: Chi-square test of independence (IOT adoption and IOT technologies).

IoT technology	Chi-square value	p-value	Significant (p<0.05)
Automated irrigation systems	10.29	0.0013	Yes
Temperature and humidity control sensors	10.29	0.0013	Yes
Soil moisture sensors	1.14	0.2850	No
Remote control *via* mobile applications	1.14	0.2850	No
AI-based crop monitoring	4.57	0.0325	Yes
Smart pest control systems	10.29	0.13	No
Cloud-based farm management platforms	10.29	0.13	No

DOF=1, *Significant at P≤0.05; NS- Non-Significant at P > 0.05.

psychological and social difficulties 68.4% of farmers were concerned about return uncertainty because they questioned the viability of payback. Decision-making risks were seen to be higher when there was a lack of local case evidence. 52.6% of traditional farmers reported having little technological skills, while the majority were unfamiliar with digital technologies. There was little confidence in running and maintaining IoT without professional assistance. In remote locations, poor internet access (42.1%) made real-time monitoring and control difficult. In conclusion high initial investment cost and lack of financial support were the most critical barriers, followed by resistance to change and uncertainty about returns, while technical skills and internet connectivity were moderate constraints.

Analysis of objective-3

To examine the economic, environmental and social impacts of IoT adoption in greenhouse farms in Oman, a Mann-Whitney U test was applied.

The results from the Mann-Whitney U test (Table 3 and 4) provides the economic, environmental and social effects of IoT-enabled greenhouse technologies versus traditional greenhouse farming in Oman. As stated in Table 3, IoT adopters rejected the null hypothesis with ample evidence for productivity ($U = 126.0$; $p<0.001$), quality ($U = 126.0$; $p<0.001$), operational cost ($U = 126.0$; $p<0.001$) and competitive advantages in the farming market ($U = 117.0$; $p<0.001$). There were more in-depth results presented in Table 4 that further suggested IoT adopters had higher productivity, better product quality, improvement in operational costs and competitive advantages in market. These findings suggest IoT technologies bring transfor-mational impacts on operational efficiency with the ability for adopters to increase output with reduced resource input. However, in regards to income as an economic variable, both Table 3 and Table 4 show no difference between IoT adopters and non-adopters ($U = 63.0$, $p = 1.000$). This suggests IoT adoption increases internal efficiencies and improving competitiveness for farmers, but it may not actually lead to increases in farmers' income right away. Possible reasons for this could be that the financial returns for farmers' use of IoT do not come on a timely basis, they reinvest their savings into farm infrastructure and there are other market influences they are subjected to beyond their control. Thus, it seems the economic benefits are counted by efficiency-based outcomes, but not on in the short-run monetary outcomes.

Regarding the environmental impacts, the results again show clear support for the adoption of IoT. As summarized in Table 3, the four key environmental variables: Reduced water usage, reduced pesticide usage, increased yield and adaptation to climate change, all found

Table 2: Barriers of adoption (Ranking method).

Barrier	Number of "Yes" responses (out of 18)	% of Traditional farmers	Rank
High initial investment cost	17	89.5%	1
Lack of financial support/Incentives	16	84.2%	2
Resistance to changing traditional practices	14	73.7%	3
Uncertain return on investment	13	68.4%	4
Lack of technical knowledge	10	52.6%	5
Poor internet connectivity	8	42.1%	6
Other barriers	4	21.1%	7

Table 3: Mann-whitney U test between groups.

Hypothesis	Dependent variables	U-statistic	p-value	Decision	Interpretation
H_{01} (Economic impact)	Productivity,	126.0	< 0.001	Reject H_{01}	Significant positive economic impacts among IoT adopters
	Quality,	126.0			
	Operational Cost,	126.0			
	Farm competitiveness	117.0			
H_{02} (Economic impact)	Income	63.0	1.000	Fail to Reject H_{01}/Accept	No significant difference in income between adopters and non-adopters
H_{03} (Environmental impact)	Water Usage Reduction,	126.0	< 0.001	Reject H_{02}	Significant positive environmental impacts among IoT adopters
	Pesticide Use Reduction,	108.0			
	Yield Increase, Climate	108.0			
	Change Adaptability	126.0			
H_{03} (Social impact)	Self-sufficiency	72.0	< 0.001	Reject H_{03}	Significant positive social impacts among IoT adopters

*Significant at $P \leq 0.05$; NS- Non-Significant at $P>0.05$.

statistical significance (U = 126.0, 108.0, 108.0 and 126.0, respectively; p<0.001). The complete results advanced in Table 4 support the argument, in which all p-values were highly significant with a range from < 0.001 to 0.0001. The findings suggest IoT technologies provide a major benefit regarding resource conservation and progressing to environmentally sustainable practices, which occurs when addressing the challenges facing Oman's agricultural landscape and particularly, a water-constrained environment. However, as noted in Table 4, the variable of 'No Benefit Observed' did find significance (U = 63.0, p = 1.000). While the overall environmental impacts found to be positive, the results indicate a number of farmers are accepting, regardless of their overall adoption of IoT, that some challenges or limited benefits remain. This raises an important point on the heterogeneity in technology adoption; specifically, farm-specific conditions and the levels of technology implemented have certain results as well.

The Mann-Whitney U test revealed a significant social impact from adopting IoT, particularly highlighting "Self-Sufficiency" as highly significant (U = 72.0, p<0.001). IoT adopters reported feeling more autonomous and confident in managing their greenhouses, which meant they relied less on outside assistance. This shows free decision making, is a clear sign of empowerment and autonomy. While immediate financial benefits were somewhat limited, there were noticeable gains in efficiency, productivity and resource management. All in all, IoT greenhouses hold great promise for boosting sustainability and resilience in Oman's agricultural systems.

RESULTS AND DISCUSSION

The study concluded that IoT-enabled greenhouse cultivation in South Al Batinah remains at its early adoption phase, since only 12% make use of such technologies while a majority utilize Traditional or hybrid approaches. Automated irrigation, temperature, crop tracking based on artificial intelligence, smart pest control, as well as cloud farm administration platforms are dominantly used by early adopters. These findings are consistent with prior research works (Li *et al*., 2020; Sharma and Kumar, 2021). There emerged a strong association between core systems, in particular between irrigation as well as environmental monitoring, which is consistent with those posited by Zhang *et al*. (2021), which noted integrated IoT systems offering more productivity gains over isolated single technologies.

Traditional farmers identified high initialization expense, lack of credit facility, resistance to change, unclear returns and technical knowledge gap as significant deterrents. These aspects are in line with literature in the past (Vasavi, *et al*., 2025), which identified cost and technical literacy as significant restrictions for technology adoption in agriculture. However, unlike some literature reporting positive definitive income gains for IoT use (Chen *et al*., 2020), this research didn't find significant farm income differences suggesting a contextual deficit at farm level which can perhaps be attributed to narrow adoption duration or limitations in scope or access issues.

Statistical analysis by the Mann-Whitney U test confirmed adopters significantly enjoyed increased productivity

Table 4: Mann-whitney U test results for IoT adoption impacts.

Variable	U-statistic	p-value	Decision	Interpretation
Economic Impact - Productivity	126.0	0.000001	Reject H_{01}	Significant difference: IoT adopters had higher productivity
Economic Impact - Quality	126.0	0.000001	Reject H_{01}	Significant difference: IoT adopters improved quality
Economic Impact - Income	63.0	1.000000	Fail to Reject H_{01}	No significant difference in income
Economic Impact - Operational cost	126.0	0.000001	Reject H_{01}	Significant reduction in operational costs for IoT adopters
Economic Impact - Farm competitiveness	117.0	0.000012	Reject H_{01}	Significant improvement in farm competitiveness
Environmental Impact - Water usage reduction	126.0	0.000001	Reject H_{02}	Significant reduction in water usage
Environmental Impact - Pesticide use reduction	108.0	0.000103	Reject H_{02}	Significant reduction in pesticide usage
Environmental Impact - Yield increase	108.0	0.000103	Reject H_{02}	Significant yield increase
Environmental Impact - Climate change adaptability	126.0	0.000001	Reject H_{02}	Significant improvement in climate adaptability
Environmental Impact - No benefit observed	63.0	1.000000	Fail to Reject H_{02}	No significant difference (some farmers did not observe benefits)
Social Impact - Self sufficiency	72.0	0.000006	Reject H_{03}	Significant improvement in self-sufficiency

*Significant at P≤0.05; NS- Non-significant at P>0.05.

improvement, product quality improvement, resource utilization improvement and social impacts including self-sufficiency, consistent with Raza *et al*. (2025). This opens up a literature gap for the Oman context, where few works studied an combined effect between socio-economic, policy and technology driving forces behind IoT adoption in greenhouse agriculture. Overall, while there is literature evidence for IoT technologies for sustainable agriculture values globally, contextual financial, technical and cultural barriers were still locally found, which is an indication towards integrated interventions specifically designed for local conditions.

CONCLUSION

As our research shows, adoption of IoT-enabled greenhouse technology by farmers in Oman is driven by access to technology as well as perceived constraints such as cost, knowledge and inadequate infrastructure. As adopters gain increased productivity and resource use efficiency, knowledge and financial constraints are cited by non-adopters as constraints holding back adoption, which opens a large diffusion inequity gap. This is strongly consistent with literature thus far and contributes further evidence towards recommending enhanced educational training, technical support, as well as financial support in order to induce adoption. Increased collaboration between policymakers, technologists, as well as research centers is needed in order to share smart agriculture solutions, knowledge, as well as scalable implementation strategies freely in order to reap full benefits of smart agriculture gains.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. The research was conducted independently, without any commercial or financial relationships that could be construed as a potential conflict of interest. All authors have read and approved the final manuscript.

REFERENCES

Agresti, A. (1996). An introduction to categorical data analysis. https://mregresion.files.wordpress.com/2012/08/agresti-introduction-to-categorical-data.pdf.

Al-Ghamdi, S.G. (2022). Smart agriculture using IoT and machine learning: A case study from Saudi Arabia. *Sustainability*. **14(15):** 9123. https://doi.org/10.3390/su14159123.

Al-Mezeini, N.K., Oukil, A. and Al-Ismaili, A.M. (2020). Investigating the efficiency of greenhouse production in Oman: A two-stage approach based on data envelopment analysis and double bootstrapping. *Journal of Cleaner Production.* **247:** 119160. https://doi.org/10.1016/j.jclepro.2019.119160.

Alsayaydeh, J., Yusof, M., Ahmad, M., Shkarupylo, V. and Herawan, S. (2023). Greenhouse horticulture automation using Arduino. *International Journal of Advanced Computer Science and Applications.* **14(10).** https://doi.org/10.14569/IJACSA.2023.0141013.

Bersani, C., Fossa, M., Priarone, A., Sacile, R. and Zero, E. (2021). Model predictive vs. relay control in energy-efficient greenhouses. *Energies.* **14(11):** 3353. https://doi.org/10.3390/en14113353.

Bewick, V., Cheek, L. and Ball, J. (2004). Statistics review 10: Further nonparametric methods. *Critical Care.* **8(3):** 196-199. https://doi.org/10.1186/cc2857.

Castro, C.D., Drumond, M.M., Batista, V.L., Nunes, A., Mancha-Agresti, P. and Azevedo, V. (2018). Vector development timeline for mucosal vaccination and treatment of disease using *Lactococcus lactis* and design approaches of next generation food grade plasmids. *Sec. Infectious Agents and Disease.* 9. https://doi.org/10.3389/fmicb.2018.01805.

Chami, D., Daccache, A. and Moujabber, M. (2020). How can sustainable agriculture increase climate resilience? A systematic review. *Sustainability.* **12(8):** 3119. https://doi.org/10.3390/su12083119.

Chen, H., Chen, A., Xu, L., Xie, H., Qiao, H., Lin, Q. and Cai, K. (2020). A deep learning CNN architecture applied in smart near-infrared analysis of water pollution for agricultural irrigation resources. *Agricultural Water Management*. **240:** 106303.

Gong, L., Yu, M. and Kollias, S. (2023). Greenhouse control using PSO-MPC for yield and energy optimization. *Algorithms.* **16(5):** 243. https://doi.org/10.3390/a16050243.

Hazmi, M., Suryaningrum, D., Umarie, I. and Swasono, M. (2023). Emerging trends in organic and eco-friendly agriculture. *West Science Interdisciplinary Studies.* **1(7):** 416-425. https://doi.org/10.58812/wsis.v1i07.124.

Hussein, A., Jabbar, K., Mohammed, A. and Jasim, L. (2024). AI and IoT in agriculture: Future harvesting. *E3S Web of Conferences.* **477:** 00090. https://doi.org/10.1051/e3sconf/2024477 00090.

Huynh, H., Tran, L. and Duong Trung, N. (2023). Smart greenhouse construction and irrigation control for optimal *Brassica juncea* development. *PLOS ONE.* ***18*(10):** e0292971. https://doi.org/10.1371/journal.pone.0292971.

Jayashankar, P., Nilakanta, S., Johnston, W., Gill, P. and Burres, R. (2018). IoT adoption in agriculture: Role of trust and risk. *Journal of Business and Industrial Marketing.* **33(6):** 804-821. https://doi.org/10.1108/JBIM-01-2018-0023.

Jepkorir, C., Mose, T. and Mwalili, T. (2022). Factors affecting IoT adoption in greenhouse farms in Kenya. *International Journal of Technology and Systems.* ***7*(2):** 1-28. https://doi.org/10.47604/ijts.1668.

Jin, X., Yu, X., Wang, X., Bai, Y., Su, T. and Kong, J. (2020). Deep learning predictor for precision agriculture using IoT. *Sustainability.* **12(4):** 1433. https://doi.org/10.3390/su12041433.

Jitea, I., Mihai, V., Arion, F., Mure'an, I. and Dumitraş, D. (2021). Innovation gaps in alternative solutions for sustainable high nature value grasslands. *Agriculture.* **11(3):** 235. https://doi.org/10.3390/agriculture11030235.

Kerkhof, L. and Keviczky, T. (2021). Predictive control of autonomous greenhouses: A data-driven approach. *ECC Proceedings*. https://doi.org/10.23919/ecc54610.2021.9655228.

Lal, G., Singh, R., Metha, R.S., Meena, N.K., Maheriya, S.P. and Choudhary, M.K. (2020). Study on irrigation levels based on IW/CPE ratio and irrigation methods on growth and yield of Fenugreek (*Trigonella foenium graecum* L.). *Legume Research-An International Journal.* **43(6):** 838-843. doi: 10.18805/LR-4050.

Lanitha, B., Poornima, E., Sudha, R., David, D.S., Kannan, K., Jegan, R. and Tesfaye, M. (2022). IoT-enabled sustainable automated greenhouse architecture with machine learning module. *Journal of Nanomaterials.* pp1-10. https://doi.org/10.1155/2022/1314903.

Li, M., Wang, J., Zhao, P., Chen, K. and Wu, L. (2020). Factors affecting the willingness of agricultural green production from the perspective of farmers' perceptions. *Science of the Total Environment*. **738:** 140289. https://doi.org/10.1016/j.scitotenv.2020.140289.

Lianying, L., Min, X., Guo, J. and Wu, F. (2024). Mechanisms influencing IoT adoption among farmers. *Scientific Reports*. **14(1).** https://doi.org/10.1038/s41598-024-65415-4.

Liu, Z., Zhang, Y., Yuan, C. *et al.* (2020). Collision avoidance and path following control of unmanned aerial vehicle in hazardous environment. *J. Intell Robot Syst.* **95:** 193-210. https://doi.org/10.1007/s10846-018-0929-y.

Mann, H.B. and Whitney, D.R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The Annals of Mathematical Statistics*. **18(1):** 50-60. https://doi.org/10.1214/aoms/1177730491.

Nachar, N. (2008). The Mann-Whitney U: A test for assessing whether two independent samples come from the same distribution. *Tutorials in quantitative Methods for Psychology*. **4(1):** 13-20. http://dx.doi.org/10.20982/tqmp.04.1.p013.

Naidu, V., Saadi, N., Hamdani, H., Moqbali, E. and Hasan, R. (2020). Open-source smart farming tools in Oman. *Journal of Student Research*. https://doi.org/10.47611/jsr.vi.968.

Narmilan, A. and Puvanitha, N. (2020). Mitigation techniques for agricultural pollution by precision technologies with a focus on the internet of things (IOTS): A review. *Agricultural Reviews*. **41(3):** 279-284. doi: 10.18805/ag.R-151.

Pandey, Y., Khan, M.F., Pandey, A.K. and Singh, S.P. (2023). Real-time soil monitoring with iot enabled system for crop prediction. *Agricultural Science Digest*. doi: 10.18805/ag.D-5705.

Rayhana, R., Xiao, G. and Liu, Z. (2020). Internet of things empowered smart greenhouse farming. *IEEE Journal of Radio Frequency Identification. **4*:** 195-211. https://doi.org/10.1109/JRFID.2020.3025093.

Raza, A., Hongliang, L., Yue, Z., Yang, T. and Wei, N. (2025). Environmental regulations and eco-innovation as catalysts for green agricultural practices: Insights from Pakistan-China agricultural cooperation. *Agricultural and Food Economics*. **13(1):** 29.

Rezvani, S. *et al*. (2020). Sensor data fusion for microclimate optimization in tomato greenhouses. *Sensors.* **20(22):** 6474. https://doi.org/10.3390/s20226474.

Rizwan, A., Khan, A., Ahmad, R. and Kim, D. (2023). Environment control using OCF for energy-efficient greenhouses. *IEEE Internet of Things Journal.* **10(6):** 5035-5049. https://doi.org/10.1109/JIOT.2022.3222086.

Rogers, E.M. (2003). Diffusion of Innovations (5th ed.). Free Press.

Shanto, S., Rahman, M., Oasik, J. and Hossain, H. (2023). Smart greenhouse monitoring using Blynk IoT app. *Journal of Engineering Research and Reports.* **25(2):** 94-107. https://doi.org/10.9734/jerr/2023/v25i2883.

Sharma, D. and Kumar, S. (2021). Internet of Things (IoT) for smart agriculture: A review of architectures, enabling technologies, challenges and future directions. *Computers and Electronics in Agriculture*. **188:** 106343. https://doi.org/10.1016/j.compag.2021.106343.

Simó, A., Dzitac, S., Duu, A. and Pandelica, I. (2023). Smart agriculture in the digital age: A comprehensive IoT-driven greenhouse monitoring system. *International Journal of Computers Communications and Control.* **18(1):** 1001.

Subahi, A.F. and Bouazza, K. (2020). An intelligent IoT-based system design for controlling and monitoring greenhouse temperature. *IEEE Access.* **8:** 125488-125500. https://doi.org/10.1109/ACCESS.2020.3006645.

Tawfeek, M.A., Alanazi, S. and El-Aziz, A.A.A. (2022). Smart greenhouse based on ANN and IoT. *Processes.* **10(2):** 241. https://doi.org/10.3390/pr10020241.

Tominaga, M., Takemura, Y., Díaz-Nájera, J., Kaishita, W., Mizoe, E. and Furukawa, T. (2024). IoT-based remote monitoring module for greenhouses. *ICAROB Proceedings*. **29:** 620-624. https://doi.org/10.5954/icarob.2024.os20-10.

Tripathy, P., Tripathy, A., Agarwal, A. and Mohanty, S. (2021). MyGreen: An IoT-enabled smart greenhouse for sustainable agriculture. *IEEE Consumer Electronics Magazine*. **10(3):** 57-62. https://doi.org/10.1109/MCE.2021.3052210.

Vasavi, S., Anandaraja, N., Murugan, P.P., Latha, M.R. and Selvi, R.P. (2025). Challenges and strategies of resource poor farmers in adoption of innovative farming technologies: A comprehensive review. *Agricultural Systems*. **227:** 104355.

Velten, S., Leventon, J., Jager, N.W. and Newig, J. (2015). What is sustainable agriculture? A systematic review. *Sustainability.* **7(6):** 7833-7865. https://doi.org/10.3390/su7067833.

Zhang, Q., Jiang, C., Li, X., Dai, S., Ying, Y. and Ping, J. (2021). Raindrop energy-based nanogenerator for intelligent greenhouses. *ACS Nano.* **15(7):** 12314-12323. https://doi.org/10.1021/acsnano.1c04258.