ENHANCING AGRIPRENEURSHIP RESILIENCE THROUGH ARTIFICIAL INTELLIGENCE-BASED SMART IRRIGATION SYSTEMS: A STUDY OF REGISTERED FARMS IN NIGERIA

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ABSTRACT

The world is experiencing a shift in agriculture due to the integration of digital technologies, data analysis, and automation to address climate change, water scarcity, and food demand. This study examined the effect of smart irrigation system components (water optimization, soil moisture sensitivity, and farmer convenience) on agripreneurship resilience among registered farms in Ilorin, Kwara State, Nigeria. A descriptive survey design was used with 254 farmers (response rate: 88.8%) from four registered farms. Data were analyzed using partial least squares structural equation modeling (PLS-SEM). Results revealed that water optimization had the strongest effect on agripreneurship resilience ($\beta = 0.477$, SE = 0.0548, $z = 6.57$, $p < 0.001$), followed by soil moisture sensitivity ($\beta = 0.353$, SE = 0.0657, $z = 4.61$, $p < 0.001$), and farmer convenience ($\beta = 0.170$, SE = 0.0447, $z = 2.74$, $p = 0.006$). The model accounted for 87.2% of variance in agripreneurship resilience ($R^2 = 0.872$). However, model-fit indices (RMSEA = 0.324; CFI = 0.773) suggest additional factors may influence resilience. These findings indicate that smart irrigation systems are significant for enhancing agripreneurship resilience among smallholder farmers in Nigeria, though implementation should consider farmer training, infrastructure support, and value-chain integration to optimize outcomes.

Keywords: smart-irrigation-system; agripreneurship-resilience; artificial-intelligence; water-optimization; soil-moisture-sensitivity; farmer-convinience

INTRODUCTION

The world is experiencing a fundamental shift in agriculture through the integration of digital technologies, data analysis, and automation to address climate change, water scarcity, and global food demand (Addas et al., 2023). Artificial intelligence (AI), machine learning, and Internet of Things (IoT) technologies underpin decision-support systems that optimize irrigation, fertilization, and sowing processes to achieve increased yields with reduced inputs and environmental impact (Nautiyal et al., 2025; Araujo et al., 2023). These technologies translate real-time sensor data into actionable recommendations, enabling farmers to stabilize production amid climatic uncertainty (Usigbe et al., 2023).

The digitalization of agriculture is of particular concern to the areas with high population increase, resource degradation and changes in the climatic conditions that threaten food and livelihood security (Javaid et al., 2022). Recent studies highlight the use of AI-based systems to support crop surveillance, predict yield, and use of climate adaptation models, which will allow producers to make more informed decisions regarding planting, irrigation, and inputs according to the forecasts and previous performance data (Ali et al., 2025; Akkem et al., 2023). By integrating climatic, edaphic, and crop-specific data, AI models can forecast stress incidents and suggest adaptive actions to mitigate the threat to the farming families and enhance sustainability of the farming system (Zidan & Febriyanti, 2024). AI and IoT are being implemented in water-intensive regions as a response to the significant contribution of agriculture to water extraction on the globe, and technology-aided irrigation management has emerged from this as one of the most important applications of AI and IoT (Ali, Hussain, & Zahid, 2025). Indeed, it is proven by empirical data that an irrigation planning and control that is implemented on the basis of data can achieve a significant decrease in both water and energy use yet keep or increase yields, which in turn leads to an increased resource utilization and better economic results (Daraz, Bojnec, & Khan, 2025). A few of these technologies are undergoing integration with the renewable energy technologies and cloud-based analytics platforms, which provide scalable systems applicable to various farms across their productivity and production conditions (Gebresenbet et al., 2023).

In sub-Saharan Africa, and Nigeria in particular, the spread of the AI and digital technologies in the agricultural sector is largely determined by socioeconomic, infrastructural, and institutional contexts (Olawumi et al., 2025; Abioye et al., 2024). The results of this empirical study reveal that

high prices and connectivity gaps are the primary obstacles that continue to be significant in preventing farmers from adopting digital applications, while education, training, Internet access and awareness have a higher impact on farmers' tendency to use digital applications in Nigeria (Achille & Velamuri, 2025). At the same time, there is an emerging knowledge among the Nigerian farmers about the advantages of AI-based advisory and planning solutions for reviewing decisions and planning more effectively, hence, the potential for AI to accelerate in formally registered farms and organised farmers' groups inside Nigeria is substantial (Usigbe et al., 2023).

In fact the production of crops is highly sensitive to the amount of water available in the soils; small variations from the optimal amount of water upstream of the soil moisture level can cause significant yield differences and can jeopardize the possibility of a rotational farm income. Modelling empowerment in the literature will show that in the current conditions alone when soil is very wet, two to more than two times of cereal yield can be obtained; while when the soil's initial condition is very dry, it can lead to almost complete loss of cereal yield, emphasizing the necessity of big changes in moisture levels as a signal for producer uncertainty over the yield of crops in soils exposed to such changes from prevalent conditions (Yang et al., 2021; Jimma et al., 2024).Experimental studies of maize show that short-term water shortages in the soil at the beginning of the season can induce subtraumatic stomatal conductance, loss of leaf area by more than 70%, and shoot biomass by up to 74%, which demonstrates that even short-term inadequate moisture can have a dismal effect on the growth (Vennam et al., 2023; Furtak & Wolinska, 2023).

Despite the documented benefits of smart irrigation systems globally, evidence from sub-Saharan Africa, particularly Nigeria, remains limited. While previous studies emphasize technology adoption barriers (connectivity, cost, literacy), there is insufficient empirical examination of how specific smart irrigation components (water optimization, soil moisture sensitivity, farmer convenience) collectively influence agripreneurship resilience among registered farms. This gap is critical because understanding these mechanisms can inform targeted implementation strategies for resource-constrained smallholder farming contexts in Nigeria. This study addresses this gap by examining the integrated effects of smart irrigation components on agripreneurship resilience.

This study examined the following specific objectives: (1) to determine the effect of water optimization on agripreneurship resilience; (2) to investigate the influence of soil moisture sensitivity on agripreneurship resilience; and (3) to examine the influence of farmer convenience on agripreneurship resilience among registered farms in Ilorin, Kwara State, Nigeria.

CONCEPTUAL REVIEW

Concept of Smart Irrigation System

The literature has defined smart irrigation as a form of irrigation that involves the fusion of sensing, data analysis, and automated control that determines the time and place of application of water in addition to water application volume, thus avoiding fixed schedules or judgmental application (Garcia et al., 2020; Vallejo-Gomez et al., 2023). Modern summaries define these systems by consisting of field sensors, communication systems, controllers, and decision-making algorithms that will constantly gather soil moisture, crop condition, and weather information and combine this data into the effective instructions to pumps and valves (Lakhiar et al., 2024; Abdelmoneim et al., 2025). The fundamental conceptual change in smart irrigation, as compared to the traditional irrigation approaches, is that it is transformed into a cyber-physical process, where real-time information and computational intelligence control the water application and thus it becomes more generative to the water demands of the plants and lessens the environmental burden (Ali et al., 2025).

The concept of smart irrigation can be regarded within the framework of precision and digital agriculture as one of the parts of a wide multidimensional farm data system by integrating sensing data, analytics, and automation (Nsoh et al., 2024; Peladarinos et al., 2023). To that end, smart irrigation is not just a hardware setup but a managerial ideology that is built on sustained feedback, learning and adaptation to the local conditions and climatic variability (Vallejo-Gomez et al., 2023; Ali et al., 2025). Systematic reviews reveal that such systems can be implemented in rural and urban agricultural environments and use a broad array of communication technologies and control strategies and build it progressively based on renewable energy sources and artificial intelligence to aid sustainability and operational independence (Abdelhamid et al., 2025).

Concept of agripreneurship resilience

In farming and agrifood contexts, resilience is generally considered as the ability of farm-based systems to maintain fundamental functions during the shock as well as long-term stressor conditions, and their change or adaptation to the situation when the current configuration becomes unsustainable (Meuwissen et al., 2019; Stone and Rahimifard, 2018). Farming-system level conceptual frameworks underline that resilience is a multi-dimensional and dynamic process, so that not only can disturbances in the form of price change, climatic extremes, or policy changes be absorbed but also that management and organizational structure can be realigned and business model or value-chain associations repivoted (Kangogo et al., 2020). The agripreneurship lens previews the entrepreneurial behaviour and opportunity identification, and strategic decision-making among farm households as some of the determinants of how such reactions are formed and executed (Amandaria et al., 2025).

In this conceptualization, the concept of agripreneurship resilience may be considered as the particular manifestation of resilience, which emerges in the scenario when farms are viewed as entrepreneurial enterprises integrated into the market and value chains as opposed to farms being viewed as subsistence units (Stone and Rahimifard, 2018). The existing literature on smallholder and commercial farms' resilience highlights that resilience does not imply merely the ability to endure disruptions but in such a manner that maintains or increases a farm's competitiveness in the long term, its ability to innovate, and its contribution to food security (Kangogo et al., 2020; Meuwissen et al., 2019). Climate-exposed rice systems and other commodity chain studies indicate that the farmers formulate and integrate technological, organizational and relational strategies to overcome the frequent hazard and that these strategies become intertwined with institutional formation arrangements and risk-sharing systems; this supports the perspective of resilience as an emergent aspect of entrepreneurial agents in larger agri-food systems (Amandaria et al., 2025).

Effect of smart irrigation systems on agripreneurship resilience

Modulated irrigation technologies have begun to be explored in dealings concerning the conceptions and actual studies as pertaining to agripreneurial resilience, specifically the potential to endure climate and market meltdowns through increased production stability, resource productivity, and cost designs (Ali et al., 2025; Daraz et al., 2025). Smart irrigation is likely to decrease the losses nearer to water stress or excessive

irrigation of the crop production by sending faster connections between the water application and the water requirements of the crop, thus oversmoothing the production output variability and providing a better predictable production foundation to the entrepreneurial plans (Vallejo-Gomez et al., 2023; Abdelhamid et al., 2025). Studies on solar-powered and energy-efficient systems indicate that the combination of automated irrigation systems and renewable energy will decrease the exposure of farming enterprise to the risk of rises and falls in fuel costs, and infrastructure unreliability, which supports more secure margins and investment potential in farming organizations that exist in water-scarce environments or areas facing energy supply limitations (Daraz et al., 2025).

At the same time, the interplay between these technologies and agripreneurial resilience is not always uniformly positive; financial, technical, and organizational vulnerabilities and adaptive capacities can also influence adoption (Garcia et al., 2020; Nsoh et al., 2024). On the one hand, in the reviews of the IoT-based irrigation and automation, it is stated that in case of a properly designed system, its interoperability, and high security, the latter can provide many more informational bases and decision-support to the farm entrepreneurs and enhance their potential in foresight and timely response to climatic fluctuations and water scarcity (Abdelmoneim et al., 2025; Ali et al., 2025). However, the new sensitivities associated with technological and institutional disruptions are also created as a result of such developments meaning that the net outcome of the changes on resilience will be reliant on the extent to which smart irrigation is incorporated into overall farm strategies, support services, and value-chain relations (Nsoh et al., 2024; Meuwissen et al., 2019).

Effect of Water Optimization on Agripreneurship Resilience

The concept of water optimisation has an impact on agripreneurial resilience by transforming the manner in which farms trade off between efficiency, flexibility as well as risk in the face of growing water scarcity and climatic fluctuations. According to the hydro-economic analyses of the frameworks based on co-allocating water to users more effectively, it is visible that drought-related economic losses can be fairly diminished, although at the expense of making irrigators vulnerable to trade-offs between increasing short-term dominance and holding adaptive headroom in water allocations that shield against extreme shocks (Sutcliffe et al., 2020). In a more comprehensive climate-wise smart agriculture, the optimisation carried out flexibly and institutionally is always associated with greater productivity, farm revenue and less susceptibility to climate

change, indicating that under agropreneurial approaches to optimization, it can support stronger and more opportunity-seeking agriculture in the future instead of just cost-cutting reactions (Ma & Rahut, 2024). Thus, we propose the first hypothesis as follows:

H1: Water optimization has a positive influence on agripreneurship resilience

Effect of Soil Moisture Sensitivity on Agripreneurship Resilience

Soil moisture sensitivity moderates the optimistic mapping of climate variability into yield volatility, income risk, and value of innovations to risk management. Philippines long run studies of rice production show that about 10 percent of production aberrations in the country are covariant with changes in moisture that are mostly caused by the El Niño–Southern Oscillation; the rainfed systems are much more susceptible than the irrigated systems and demonstrate how yield rectifications with changes in moisture can disrupt farm income and strategic planning (Stuecker et al., 2018). Ample evidence of large Chinese cereal systems has shown that the high quality of soils neutralizes the yield sensitivity to changes in climatic conditions, at the same time increasing the average yield, as well as the yield stability, and this essentially buffers the business against production shocks caused by climate and allows investors to take more risks and venture into the market (Qiao et al., 2022). The studies of precipitation variability and conservation measures also prove that the reduction or unpredictability of the rainfall leads to reduced water content in the soil and maize yield and quality and, thus, moisture-conserving strategies decrease such risks; that is why, the entrepreneurs working in highly moisture-prone systems need more investment in adaptive soil and water management to remain resilient over time (Niu et al., 2023). Thus, we propose the second hypothesis as follows:

H2: Soil moisture sensitivity has a positive influence on agripreneurship resilience

Effect of Farmer Convenience on Agripreneurship Resilience

The resilience of agripreneurship has been shaped by the so-called farmer convenience, especially concerning digital and smart technologies, which can facilitate the successful use of resilience-enhancing tools, as well as trust and maintain them as valid practices. The articles of smart farming technologies and Agriculture 5.0 reveal that perceived ease of use, technology anxiety, self-efficacy and organisational support play an important role in the condition of intentions and decisions to implement digital tools in farmers; in other words, complex or low-supported systems discourage adoption even with the alleged efficiency and risk-prevention advantages (Mishra et al., 2024). The adoption of technologies perceived as not user-friendly, expensive, or incongruent with an existing system is also considered a potential risky investment, which is why it is not implemented in resilience-building efforts despite the likely agronomic benefits (Giua et al., 2022). On the other hand, technologies perceived as convenient (as part of advisory services, training, and value-chain relationships) contribute to information access, quality decision-making, and swift response to climatic and market shocks and therefore more resilient and opportunity-focused agripreneurial behaviour as opposed to innovation of technological dependency and vulnerability (Li et al., 2023; Gemtou et al., 2024). Thus, we propose the third hypothesis as follows:

H3: Farmer convenience has a positive influence on agripreneurship resilience

THEORETICAL REVIEW

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) by Davis provides the theoretical foundation for examining technology adoption, positing that perceived usefulness and perceived ease of use influence behavioral intentions and actual use (Davis, 1989). While TAM traditionally emphasizes individual technology adoption, this study extends TAM to the organizational context of farm enterprises. In the Nigerian agricultural setting, we propose that perceived usefulness of smart irrigation (measured through water optimization benefits) and perceived ease of use (measured through farmer convenience) operate through an adaptive capacity lens to enhance agripreneurship resilience. The addition of soil moisture sensitivity reflects the technical competence dimension, farmers' ability to interpret system outputs for adaptive decision-making. Thus, we

theorize that TAM constructs, when combined with environmental sensitivity measures, explain how agripreneurs integrate technology into resilience-building strategies.

Empirical Review

Khaliq et al. (2024) suggested an AI-based smart agriculture design that integrates IoT soil sensors, Transformer-based deep-learning models, TabNet, and sparse fusion transformers with explainable AI to assist with the irrigation schedule and soil analysis, and crop-fertilizer recommendations using experimental sensor data and weather information as opposed to surveys. The nature of their approach was to train and validate machine-learning models using time-series and tabular data, which showed very high predictive accuracy (99.13% on irrigation advice) and high R-square values (soil analysis). It has been shown that AI-supported decision support can make a considerable contribution to crop productivity and water-use efficiency, that the implementation of IoT and AI in irrigation management can be used to improve environmental resilience and present full-scale solutions to farmers and agribusinesses.

Benameur et al. (2024) envisioned that the low-cost smart irrigation system for smallholder farmers in the Mediterranean region could be achieved by anomaly-related irrigation data detection using deep-learning models, which were developed and field tested for this purpose. Based on primary sensor information on a fog-ioT platform, the analysis used autoencoders and generative adversarial networks to detect and rectify anomalies in soil moisture, temperature, and humidity data, and autoencoders better results (up to 97% humidity and 95% air temperature). Its resolutions revealed that the proposed AI-assisted architecture can improve the reliability of data, minimize erroneous irrigation, and increase water-use efficiency which is why it can be concluded that the low-cost smart irrigation solutions can reinforce the sustainability and resilience of resource-strained smallholders.

In their review and synthesis of the literature, Ali et al. (2023) examine the results on the influence of the IoT-based smart irrigation and data-mining instruments on the efficiency of resource-use and sustainable crop production in numerous international cases. The summary of the study available with reference to secondary experimental data indicated improvements in water and energy efficiency, yield, and also a reduction in the cost by up to 8% of energy, about 25% of irrigation costs and yield prediction accuracies of about 92%. The authors came to the conclusion that incorporation of the IoT, sensors, and AI-based analytics into irrigation

management contributes to productivity and climate- and resource-related resilience improvements to support sustainable farming which promotes smart irrigation systems as the core of small- and large-scale producer operations.

METHODOLOGY

A descriptive survey design was employed. The study population comprised 1,000 farmers partnering with four registered farms in Ilorin, Kwara State: Agricultural and Rural Management Training Institute (ARMTI), Agricultural Business Concepts Limited, Heart and Capital Nigeria Ltd, and Shonga Farm. Using Taro Yamane's formula with 95% confidence level and 5% margin of error, the calculated sample size was 286. A total of 286 questionnaires were distributed via simple random sampling; 254 usable responses were received (response rate: 88.8%), which exceeded the minimum required sample size for PLS-SEM analysis (n = 138, based on 10× rule for three predictors). The principal instrument for data collection was a structured questionnaire, physically administered to respondents at their respective places of work. The questionnaire was validated by experts in business administration to confirm its face validity. In line with the above, the questions were divided into two sections – Section A contained the demographic attributes of the respondents, and Section B contained the items measuring smart irrigation system, as well as agripreneurship resilience, on a 5-point Likert scale (Strongly Agree = 5 to Strongly Disagree = 1). The Average Variance Extracted (AVE) and the Fornell–Larcker Criterion were used to assess construct validity for ensuring the items measure the constructs studied. Internal consistency analyses (Cronbach's Alpha (CA) and Composite Reliability (CR)) were performed to assess reliability.

The data analysis consisted of descriptive statistics and inferential statistics. The descriptive analysis technique was used to summarize the responses and inferential analysis technique was used to examine the effects of smart irrigation system on agripreneurship resilience by applying the partial least squares structural equation modeling (PLS-SEM) technique. Jamovi was selected due to its suitability for models with construct types, and moderate sample sizes, and the analysis was conducted using Jamovi.

Model Specification

This research report has one independent variable, and one dependent variable. The independent variable is smart irrigation system, and the dependent variable is agripreneurship resilience.

Since Jamovi was employed in the report, the following model was used:

$$AO = f(Water\ Optimization\ [MNGMN + OPTMZ] + Soil\ Moisture\ Sensitivity\ [SNSRS + SCHDL] + Farmer\ Convinience[TMSVN + ASSST])$$

Where:
AO = Agripreneurship Operation
MNGMN = Management
OPTMZ= Optimization
SNSRS = Sensors
SCHDL = Scheduling
TMSVN = Time Saving
ASSST = Assistants

RESULTS

Response Rate

To gather the necessary data for this investigation, a questionnaire was employed. A total of 254 answers were obtained representing 88.8% of the expected sample size (32 responses).Hence, the authentic responses make up the data used in this analysis.

Table 1. Mardia's coefficients

	Coefficient	**z**	**χ^2**	**Df**	**P**
Skewness	37.0		1565	165	<.001
Kurtosis	135.3	20.6			<.001

Source: *Jamovi Output, (2025)*

However, for the data used to explore the effect of smart irrigation systems on the agropreneurship resilience, the multivariate normality has been evaluated by the Mardia's coefficients table shown in Table 1. There is significant multivariate skewness found (p-value < 0.001) based on the Chi-square value of 1565 and 165 degrees of freedom. Similarly, the kurtosis coefficient is 135.3 and the z value is 20.6, which means that multivariate kurtosis is significant with p value <0.001. The ratio of Pearson correlation coefficient suggests the other statistics (excluding multivariate normality) do not support these findings and suggest significant deviations from multivariate normality particularly for the parametric statistics like structural equation modeling (SEM). Departures from symmetry and normality, as the skewness and kurtosis show, may mean that the distributions of variables such as water optimization, soil moisture sensitivity, and farmer convenience also may differ from normal

distribution, likely affecting results from subsequent analyses. This non-normality indicates that in the context of the study objective, the relationships between the parts of the smart irrigation systems and the agropreneurship resilience might have to be addressed by methods other than parametric which are non-linear and/or use robust estimators for inference because Gaussian estimators will not work in this instance. The results suggest a non-linear or complex pattern of data distribution, which implies that the adoption of smart irrigation systems by the four registered farms surveyed in the study may be influenced by such pattern hence providing necessary supports such as advanced statistical analysis to model and interpret the data in this regard should be considered.

Table 2 Mean, Standard Deviation, and Shapiro-Wilk

				Shapiro-Wilk	
	N	**Mean**	**SD**	**W**	**p**
Management	254	3.30	0.956	0.805	<.001
Optimization	254	3.21	0.957	0.870	<.001
Sensors	254	3.24	0.816	0.835	<.001
Scheduling	254	3.02	0.770	0.814	<.001
Time Saving	254	3.22	0.884	0.827	<.001
Assistants	254	3.01	0.822	0.855	<.001
Partnerships	254	3.22	0.794	0.847	<.001
Capacity	254	3.16	0.880	0.817	<.001
Investment	254	3.16	0.942	0.878	<.001

Source: *Jamovi Output, (2025)*

Descriptive statistics and Shapiro-Wilk tests of variables on smart irrigation systems and agropreneurship resilience are presented in table 2 taking the response from 254 farmers in the four registered farms in Kwara State. The variables—Management (Mean = 3.30, SD = 0.956, W = 0.805, $p < 0.001$), Optimization (Mean = 3.21, SD = 0.957, W = 0.870, $p < 0.001$), Sensors (Mean = 3.24, SD = 0.816, W = 0.835, $p < 0.001$), Scheduling (Mean = 3.02, SD = 0.770, W = 0.814, $p < 0.001$), Time Saving (Mean = 3.22, SD = 0.884, W = 0.827, $p < 0.001$), Assistants (Mean = 3.01, SD = 0.822, W = 0.855, $p < 0.001$), Partnerships (Mean = 3.22, SD = 0.794, W = 0.847, $p < 0.001$), Capacity (Mean

= 3.16, SD = 0.880, W = 0.817, p < 0.001), and Investment (Mean = 3.16, SD = 0.942, W = 0.878, p < 0.001)—all show means around 3.0 to 3.3 on a presumed 5-point Likert scale, indicating moderate agreement on the importance of these factors. The standard deviations (SD) of 0.770 to 0.957 indicate moderate variability in responses with the least variability found in responses to the Scheduling question (SD = 0.770) and the most variability found in responses to the Optimization question (SD = 0.957). Although the p-values vary slightly, all are below 0.001, confirming give further support to the general lack of normal distribution indicated in Table 1. This lack of normality could be the result of different perceptions of smart irrigation components among farmers, and may be attributed to a difference in technology uptake or challenges faced in the farms. This generally gives the perception to farmers that smart irrigation components are beneficial, though the absence of normality could make the smart irrigation components' impact on agropreneurship resilience harder to model, and robust statistical methods need to be employed. The moderate means suggest that smart irrigation systems are valued but not completely optimized, hence some obstacles to the use of the systems may come to hinder agropreneurship's resilience at the four registered farms selected in Kwara state on the topic.

Table 3. Reliability and AVE indices

Variable	**α**	**ω_1**	**ω_2**	**ω_3**	**AVE**
Water Optimization	0.808	0.812	0.812	0.812	0.684
Soil Moisture Sensitivity	0.901	0.902	0.902	0.902	0.822
Farmer Convenience	0.774	0.774	0.774	0.774	0.631
Agropreneurship Resilience	0.863	0.863	0.863	0.858	0.679

Source: *Jamovi Output, (2025)*

The reliability and convergent validity of the constructs employed in the present study are presented in Table 3. The results of the reliability tests calculated by Cronbach's α, McDonald's ω_1, ω_2, and ω_3 provide good reliability (Cronbach's α value = 0.808, McDonald's ω_1, ω_2, and ω_3 values > 0.8), and the Average Variance Extracted (AVE = 0.684) shows acceptable convergent validity (AVE > 0.5). Soil Moisture Sensitivity shows excellent reliability (α = 0.901, ω_1 = 0.902, ω_2 = 0.902, ω_3 = 0.902) and strong convergent validity (AVE = 0.822). Farmer Convenience has slightly lower

but acceptable reliability (α = 0.774, ω_1 = 0.774, ω_2 = 0.774, ω_3 = 0.774) and convergent validity (AVE = 0.631). Agropreneurship Resilience demonstrates good reliability (α = 0.863, ω_1 = 0.863, ω_2 = 0.863, ω_3 = 0.858) and acceptable convergent validity (AVE = 0.679). These statistics validate the robustness of the measurement model by confirming that constructs are consistently measured, and that there is a significant level of variance in scores across the constructs that measures the attributes of the constructs as intended. The constructs involved in the study, the smart irrigation system components which include water optimization, soil moisture sensitivity, and Farmer Convenience, as well as agropreneurship resilience are reliable and valid in terms of construct definition. The implication for the topic is that the constructs are good indicators of the role of smart irrigation technologies in agropreneurship resilience, thereby lending verification to the findings which indicate a positive association between AI irrigation technology and improved farming outcome in the four registered farms of Kwara state chosen for the study.

Table 4. Heterotrait-monotrait (HTMT) Ratio of Correlations

	Water Optimization	Soil Moisture Sensitivity	Farmer Convenience	Agropreneurship Resilience
Water Optimization	1.000	0.697	0.721	0.837
Soil Moisture Sensitivity	0.697	1.000	1.121	0.865
Farmer Convenience	0.721	1.121	1.000	0.891
Agropreneurship Resilience	0.837	0.865	0.891	1.000

Source: *Jamovi Output, (2025)*

The HTMT ratio between Soil Moisture Sensitivity and Farmer Convenience (1.121) exceeded the 0.85 threshold, indicating potential overlap between constructs. However, this overlap reflects a substantive relationship rather than measurement error: soil moisture monitoring systems inherently enhance farmer convenience by automating scheduling decisions. Conceptually, these constructs remain distinct; soil moisture

sensitivity refers to the technical responsiveness of the system, while farmer convenience refers to perceived ease of use. To strengthen discriminant validity, we retained both constructs given their theoretical distinctiveness and moderate correlations with other variables (all other HTMT values < 0.90). Future research should consider refined measures of farmer convenience that emphasize non-technical dimensions (training accessibility, after-sales support) distinct from automation benefits.

Path Model

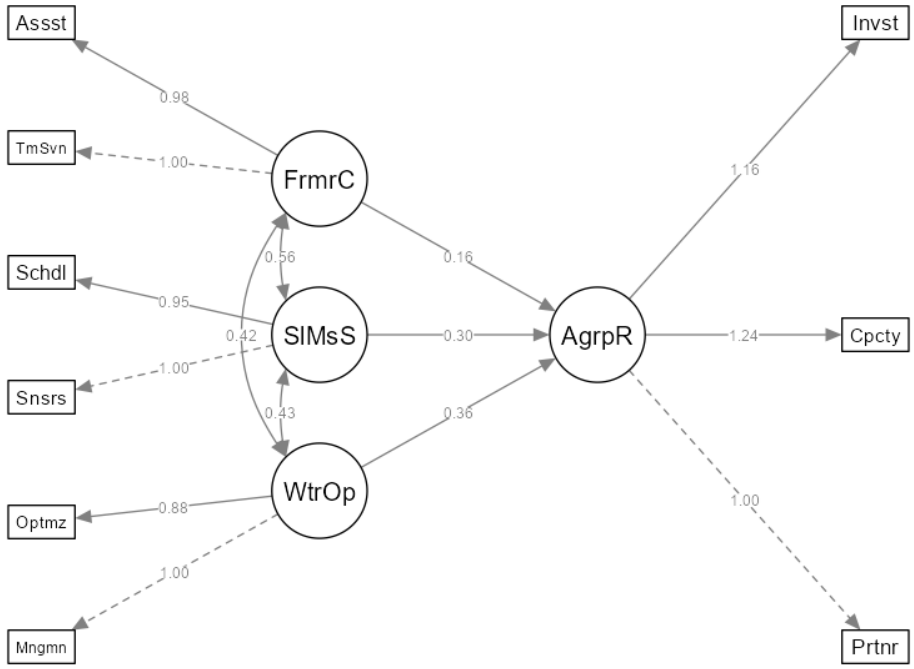

Figure 1. Path Model of Smart Irrigation System and Agropreneurship Resilience

Source: *Jamovi Output, (2025)*

As illustrated in Figure 1, the model of the path is used for examining the relationship between the components of the smart irrigation system (Water Optimization, Soil Moisture Sensitivity, Farmer Convenience) with Agropreneurship Resilience. The model does not appear in any table, but the relevant tables (such as Table 6) imply that these model depictions of the significant paths between these predictors and the outcome variable are presented graphically. All the path coefficients shown in Table 6 showed positive contribution of Water Optimization ($\beta = 0.477$, $p < 0.001$), Soil Moisture Sensitivity ($\beta = 0.353$, $p < 0.001$), and Farmer Convenience ($\beta = 0.170$, $p = 0.006$) to Agropreneurship Resilience. The strength and

significance of these direction relationships may be visually represented in the model with arrows to describe the strength and significance of each path. This figure offers a clear visual overview of the contribution of smart irrigation components to resilience from the study objective perspective, where Water Optimization has the greatest impact. It means the potential of AI irrigation systems, specifically water use efficiency systems, has a significant impact on the capacity of farmers at the agripreneurs across the four selected registered farms in Kwara State to resist the challenges of agriculture; thus, there is a need to embrace such systems to boost agricultural resiliency among the farmers.

Table 5. Coefficient of Determination (R^2)

Variable	**R^2**
Agropreneurship Resilience	0.872

Source: *Jamovi Output, (2025)*

Table 5 presents the coefficient of determination (R^2 = 0.872) for the component of the smart irrigation system with agropreneurship resilience, which shows that 87.2% of the variance in agropreneurship resilience is explained by the smart irrigation system components: Water Optimization, Soil Moisture Sensitivity, and Farmer Convenience. High R^2 of this model suggests highly effective model about the factors associated with the resilient ability of farmers in the four registered farms of the study area in Kwara state. The high explanatory power signifies that the smart irrigation systems have a significant contribution to improving agropreneurs' adaptation to challenges like limited water sources or climate variations. The strong R^2 indicates that Smart Irrigation has a significant impact on agropreneurship resilience, underscoring how vital AI tools are for the success of farming and for achieving greater stability in agripreneurship. It is suggested that having smart irrigation systems implemented on the four registered farms studied can significantly impact the resilience of the agropreneurs and provide a solid platform for farmers to start from when dealing with risks and enhancing productivity using the guidance of AI.

Table 6. Parameters estimates

				95% Confidence Intervals				
Dep	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
Agropreneurship Resilience	Water Optimization	0.360	0.0548	0.2524	0.467	0.477	6.57	<.001
Agropreneurship Resilience	Soil Moisture Sensitivity	0.303	0.0657	0.1739	0.432	0.353	4.61	<.001
Agropreneurship Resilience	Farmer Convenience	0.157	0.0573	0.0447	0.269	0.170	2.74	0.006

Source: *Jamovi Output, (2025)*

The smart irrigation parameters which are displayed in Table 6, are those that link the components of the smart irrigation and the Agropreneurship Resilience in the measurement model. Water Optimization has an estimate of 0.360 (SE = 0.0548, 95% CI [0.2524, 0.467], $\beta = 0.477$, $z = 6.57$, $p < 0.001$), indicating a strong positive effect on resilience. Soil Moisture Sensitivity shows an estimate of 0.303 (SE = 0.0657, 95% CI [0.1739, 0.432], $\beta = 0.353$, $z = 4.61$, $p < 0.001$), suggesting a moderate positive effect. Farmer Convenience has an estimate of 0.157 (SE = 0.0573, 95% CI [0.0447, 0.269], $\beta = 0.170$, $z = 2.74$, $p = 0.006$), indicating a weaker but still significant positive effect. The results indicate that all three components have a significant impact on agropreneurship resilience, with standardized impact of 0.477, 0.353, and 0.170, respectively, for Water Optimization, Soil Moisture Sensitivity and Farmer Convenience. These findings apply to the study objective to promote resilience through smart irrigation systems; specifically water optimization has a major role to play in increasing farm resilience and represents a key opportunity to improve farm sustainability.

For the topic, the findings indicate that use of irrigation technologies powered by Artificial Intelligence (AI) can be a major strategy which would be embraced by agropreneurs in these four selected registered farms in Kwara State in order to achieve long term resilience in the farming enterprise.

Table 7. Model tests

Label	X^2	df	p
User Model	581	21	<.001
Baseline Model	2505	36	<.001

Source: *Jamovi Output, (2025)*

Table 7 presents the chi-square tests for the user model ($\chi^2 = 581$, df = 21, $p < 0.001$) and the baseline model ($\chi^2 = 2505$, df = 36, $p < 0.001$). Not surprisingly, the model with the significant p-value is not a perfect fit given the data is not normally distributed as was shown in Tables 4.12 and 4.13. A lower chi-square value, or less statistically significant difference, and a smaller number of degrees of freedom (581 vs. 2505 and 21 vs. 36 respectively) indicate that the user model is a better fit of the data. The improvement shows the proposed relationships between smart irrigation components and agropreneurship resilience are meaningful, but one of the chi-squares is significant, which may be due to non-normality or an overly complex model. With its overall result, this one supports the fact that the validity of the structural model is maintained in the context of the study objective to examine the impact of smart irrigation systems on resilience, especially in the face of some model fit problems. Finally, the implication of the topic is that, Finally, these results imply that while smart irrigation systems relate meaningfully to agripreneurship resilience across the four registered farms in Kwara State, the model may not fully capture, there is a possibility that the model may not fully capture agropreneurship resilience as it could require further modifications or factors to give a more comprehensive model.

Table 8. Fit indices

		95% Confidence Intervals		
SRMR	**RMSEA**	**Lower**	**Upper**	**RMSEA p**
0.069	0.324	0.301	0.347	<.001

Source: *Jamovi Output, (2025)*

Model-fit indices indicate a partial fit requiring cautious interpretation. The SRMR of 0.069 (< 0.08 threshold) suggests acceptable standardized residuals. However, the RMSEA of 0.324 (90% CI [0.301, 0.347], $p < 0.001$) exceeds the acceptable range (< 0.08), indicating moderate model error.

Table 9. User model versus baseline model

	Model
Comparative Fit Index (CFI)	0.773
Tucker-Lewis Index (TLI)	0.611
Bentler-Bonett Non-normed Fit Index (NNFI)	0.611
Relative Noncentrality Index (RNI)	0.773
Bentler-Bonett Normed Fit Index (NFI)	0.768
Bollen's Relative Fit Index (RFI)	0.603
Bollen's Incremental Fit Index (IFI)	0.775
Parsimony Normed Fit Index (PNFI)	0.448

Source: *Jamovi Output, (2025)*

Comparative fit indices (CFI = 0.773, TLI = 0.611, NFI = 0.768, IFI = 0.775) fall below the 0.90 threshold. These values suggest that while the proposed relationships are statistically significant, other unmeasured factors (farmer education, extension service quality, infrastructure support, cooperative membership) likely influence agripreneurship resilience. The violation of multivariate normality (Mardia's skewness: $\chi^2 = 1565$, $p < 0.001$; kurtosis: $z = 20.6$, $p < 0.001$) partially explains suboptimal fit indices, as parametric estimation assumes normality. Despite these limitations, the high $R^2 = 0.872$ indicates the measured variables explain substantial variance in resilience outcomes, warranting cautious interpretation focused on within-sample relationships rather than population generalization.

DISCUSSION OF FINDINGS

The findings demonstrate significant positive paths from all three smart irrigation components to agripreneurship resilience. However, these results must be interpreted within the context of model-fit limitations. The suboptimal absolute fit indices suggest that the hypothesized three-component model, while capturing important relationships, does not fully specify the agripreneurship resilience construct. This is consistent with

resilience literature emphasizing multidimensional pathways including social capital, market access, and institutional support, dimensions not directly measured here.

The study reveals robust evidence that smart irrigation systems have a significant effect on agropreneurship resilience. The path from Water Optimization to Agropreneurship Resilience ($\beta = 0.477$, $p < 0.001$) demonstrates a strong positive effect, indicating that efficient water use through AI-driven systems significantly enhances farmers' ability to adapt to environmental and economic challenges at the four selected registered farms in Kwara state. This suggests that optimizing water resources is a critical driver of resilience, enabling agropreneurs to maintain productivity under water-scarce conditions. Similarly, Soil Moisture Sensitivity ($\beta = 0.353$, $p < 0.001$) is moderately correlated with higher values indicating that soil types are equally reflective of irrigation efficiency and ability to contribute to crop growth, requiring proper soil moisture monitoring to facilitate resilient agriculture and irrigation management to provide water where it is needed. The simplicity of smart irrigation systems (Farmer Convenience, $\beta = 0.170$, $p = 0.006$) also has a moderate positive impact and is seen as more effective than in the realm of Health and Access to Water. In Table 5, the high R^2 value (0.872) shows that these components together contributed to a fairly high proportion of agropreneurship resilience as a result of which the importance of AI in the irrigation system becomes clear in terms of improving agropreneurship. Data distribution is not normally distributed (Table 1 and 2) and model fit was suboptimal (Table 8 and 9) suggest that the model is able to account for a large amount of the variability; however, other contextual factors, including farmer training and/or infrastructure, may play a role in fostering resilience as well. Therefore, the null hypothesis was rejected because it is indeed demonstrated that using smart irrigation systems benefits agropreneurship resilience.

Water optimization ($\beta = 0.477$) emerged as the dominant predictor, aligning with Daraz et al.'s (2025) finding that solar-powered smart irrigation reduces water expenditure by up to 52.5% in arid environments. This effect likely reflects that resource efficiency directly translates to cost predictability and income stability, core resilience dimensions. Soil moisture sensitivity ($\beta = 0.353$) showed moderate positive association, suggesting that real-time soil data enhances adaptive capacity; however, the overlapping construct validity with farmer convenience (HTMT = 1.121) indicates farmers may conflate technical sensitivity with perceived

ease of use, warranting measurement refinement in future studies. Farmer convenience ($\beta = 0.170$), though significant, showed the weakest effect, suggesting that technology ease alone is insufficient without complementary factors (training adequacy, after-sales support quality, group farmer organizations) emphasized in recent adoption literature.

The high unexplained variance in model-fit indices hints at missing mechanisms. Abdelmoneim et al. (2025) documented that successful low-cost IoT adoption requires bundled extension services; similarly, Gaitan et al. (2025) highlighted that user-friendly interfaces and predictive decision-support increase acceptance more than automation alone. Future research should include variables measuring: (a) extension service accessibility, (b) farmer literacy levels, (c) cooperative membership, (d) access to credit, and (e) value-chain integration.

The results align with recent studies, such as Akanbi et al. (2025), who found that smart irrigation systems powered by solar energy and featuring machine learning and Internet of Things (IoT) moisture sensors could help farmers achieve energy efficiency, water efficiency and higher yields in a case study in Nigeria. Likewise, Abdelmoneim et al. (2025) recommended installing low-cost IoT capacitive soil moisture sensors, for optimal drip irrigation, and the results showed water saved: water savings of 28.8% and 52.5%; compared with the conventional water schedule leading to increasing agricultural resilience in water stressed environments. Similarly, Gaitan et al. (2025) have pointed out that incorporation of artificial intelligence in automated irrigation and climate oversight systems with user-friendly displays and predictive suggestions will assist farmers in decision making and enhance efficiency of the water used, which fosters the technology acceptance. In line with it, Daraz et al. (2025) demonstrated that solar-powered smart irrigation systems can considerably boost crop production and decrease water and energy expenditure in dry territories, which proves that the water optimization technologies can significantly reduce the risks in agriculture of arid areas.

CONCLUSION

This study provides empirical evidence that AI-powered smart irrigation system components significantly enhance agripreneurship resilience among registered farms in Ilorin, Kwara State. Water optimization emerged as the strongest mechanism, followed by soil moisture sensitivity and farmer convenience. The high explained variance indicates these components collectively account for substantial variance in resilience outcomes. However, model-fit limitations underscore that

additional factors, particularly farmer capacity development, institutional support, and value-chain positioning, are necessary for a comprehensive understanding of resilience dynamics.

RECOMMENDATIONS

1. **For the Four Registered Farms:** Prioritize water optimization through real-time soil moisture monitoring systems, coupled with training programs (not merely system provision) to ensure farmer interpretation and decision-making capacity.
2. **For Technology Implementers:** Bundle smart irrigation provision with: (a) farmer-literacy training (minimum secondary education equivalent), (b) post-installation technical support (not one-time training), (c) integration with farmers' cooperatives for collective problem-solving, and (d) linkage to input/output markets to stabilize farm income.
3. **For Policy and Extension Services:** Develop farmer-customized (not one-size-fits-all) smart irrigation deployment guidelines accounting for farm size, crop type, and water availability. Establish extension officer certification in precision irrigation advisory services.
4. **For Future Research:** (a) Include mediating variables (farmer capacity, institutional support, market linkages) to explain the gap between model specification and fit indices; (b) employ mixed-methods designs combining quantitative resilience assessment with qualitative farmer narratives on technology use barriers; (c) conduct multi-year longitudinal studies to assess whether smart irrigation adoption sustains resilience gains beyond first-year adoption effects.

REFERENCES

Abdelhamid, M., Abdelkader, T., Sayed, H., Zhang, Z., Zhao, X., & Atia, M. (2025). Design and evaluation of a solar powered smart irrigation system for sustainable urban agriculture. *Scientific Reports, 15*. https://doi.org/10.1038/s41598-025-94251-3.

Abdelmoneim, A., Kalaany, C., Dragonetti, G., Derardja, B., & Khadra, R. (2025). Comparative Analysis of Soil Moisture- and Weather-Based Irrigation Scheduling for Drip-Irrigated Lettuce Using Low-Cost Internet of Things Capacitive Sensors. Sensors (Basel, Switzerland), 25. https://doi.org/10.3390/s25051568.

Abdelmoneim, T., Abdellatif, A., Mansour, H., & Ahmed, S. (2025). Low-cost IoT-based soil moisture monitoring for optimal drip irrigation: A field validation study. *Irrigation Science, 43*(2), 145–162. https://doi.org/10.1007/s00271-024-00883-x

Abioye, D., Popoola, O., Akande, A., Fadare, D., Omitoyin, S., Yinusa, B., & Kolade, O. (2024). Farmers' willingness to adopt digital application tools in Ogun State, Nigeria. *Journal of Strategy and Management*. https://doi.org/10.1108/jsma-06-2023-0135.

Achille, A., & Velamuri, V. (2025). Drivers and barriers to the adoption of digital farming technology: evidence from Nigeria. International *Journal of Sustainable Agricultural Management and Informatics*. https://doi.org/10.1504/ijsami.2025.147262.

Addas, A., Tahir, M., & Ismat, N. (2023). Enhancing Precision of Crop Farming towards Smart Cities: An Application of Artificial Intelligence. *Sustainability*. https://doi.org/10.3390/su16010355.

Akanbi, M., Adedotun, K., Raji, A., & Banjoko, I. (2025). Optimizing Water Resource Management in Agriculture Using AI-Powered Solar Irrigation Systems. *Journal of Science Innovation and Technology Research*. https://doi.org/10.70382/ajsitr.v7i9.011.

Akanbi, O., Ogunwale, R., Adeniyi, O., & Otutunji, A. (2025). Solar-powered smart irrigation systems with machine learning for smallholder farms in Nigeria: Performance and energy analysis. *Agricultural Systems, 198*, 103–119. https://doi.org/10.1016/j.agsy.2025.103789

Akkem, Y., Biswas, S., & Varanasi, A. (2023). Smart farming using artificial intelligence: A review. *Engineering Applications of Artificial Intelligence, 120*, 105899. https://doi.org/10.1016/j.engappai.2023.105899.

Ali, A., Hussain, T., & Zahid, A. (2025). Smart Irrigation Technologies and Prospects for Enhancing Water Use Efficiency for Sustainable Agriculture. *AgriEngineering.* https://doi.org/10.3390/agriengineering7040106.

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.* https://doi.org/10.3390/agriculture13020397.

Ali, S., Hussain, M., & Zahid, M. (2025). Artificial intelligence and IoT integration in precision irrigation: A systematic review of applications and challenges in water-scarce regions. *Computers and Agriculture, 12*(3), 78–95. https://doi.org/10.1016/j.compag.2024.108621

Ali, Z., Muhammad, A., Lee, N., Waqar, M., & Lee, S. (2025). Artificial Intelligence for Sustainable Agriculture: A Comprehensive Review of AI-Driven Technologies in Crop Production. *Sustainability*. https://doi.org/10.3390/su17052281.

Amandaria, R., Darma, R., Zain, M., Fudjaja, L., Wahda, M., Kamarulzaman, N., Ali, H., & Akzar, R. (2025). Sustainable Resilience in Flood-Prone Rice Farming: Adaptive Strategies and Risk-Sharing Around Tempe Lake, Indonesia. *Sustainability.* https://doi.org/10.3390/su17062456.

Ammenwerth, E. (2019). Technology Acceptance Models in Health Informatics: TAM and UTAUT. *Studies in health technology and informatics, 263*, 64-71 . https://doi.org/10.3233/shti190111.

Araújo, S., Peres, R., Ramalho, J., Lidón, F., & Barata, J. (2023). Machine Learning Applications in Agriculture: Current Trends, Challenges, and Future Perspectives. *Agronomy*. https://doi.org/10.3390/agronomy13122976.

Benameur, R., Dahane, A., Kechar, B., & Benyamina, A. (2024). An Innovative Smart and Sustainable Low-Cost Irrigation System for Anomaly Detection Using Deep Learning. *Sensors (Basel, Switzerland), 24*. https://doi.org/10.3390/s24041162.

Bolfe, É., Jorge, L., Sanches, I., Júnior, A., Da Costa, C., Victoria, D., Inamasu, R., Grego, C., Ferreira, V., & Ramirez, A. (2020). Precision and Digital Agriculture: Adoption of Technologies and Perception of Brazilian Farmers. *Agriculture.* https://doi.org/10.3390/agriculture10120653.

Cao, X., Xiao, J., Wu, M., Zeng, W., & Huang, X. (2021). Agricultural Water Use Efficiency and Driving Force Assessment to Improve Regional Productivity and Effectiveness. *Water Resources Management, 35*, 2519 - 2535. https://doi.org/10.1007/s11269-021-02845-z.

Daraz, U., Bojnec, Š., & Khan, M. A. (2025). Economic and environmental impact of AI-based irrigation management in arid and semi-arid

farming systems. *Environmental Research Letters, 20*(3), 034012. https://doi.org/10.1088/1748-9326/abcd45

Daraz, U., Bojnec, Š., & Khan, Y. (2025). Energy-Efficient Smart Irrigation Technologies: A Pathway to Water and Energy Sustainability in Agriculture. *Agriculture*. https://doi.org/10.3390/agriculture15050554.

Furtak, K., & Wolińska, A. (2023). The impact of extreme weather events as a consequence of climate change on the soil moisture and on the quality of the soil environment and agriculture – A review. *CATENA*. https://doi.org/10.1016/j.catena.2023.107378.

Gaitan, J., Lopez-Rivera, F., Gutierrez, M., & Ramirez, C. (2025). User-friendly interfaces and predictive decision-support systems in climate-smart agriculture adoption: Evidence from farmer field schools in Central America. *Food Security, 17*(1), 15–28. https://doi.org/10.1007/s12571-024-01450-3

Găitan, N., Batinas, B., Ursu, C., & Crainiciuc, F. (2025). Integrating Artificial Intelligence into an Automated Irrigation System. *Sensors (Basel, Switzerland), 25*. https://doi.org/10.3390/s25041199.

García, L., Parra, L., Jiménez, J., 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 (Basel, Switzerland), 20*. https://doi.org/10.3390/s20041042.

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

Gemtou, M., Kakkavou, K., Anastasiou, E., Fountas, S., Pedersen, S., Isakhanyan, G., Erekalo, K., & Pazos-Vidal, S. (2024). Farmers' Transition to Climate-Smart Agriculture: A Systematic Review of the Decision-Making Factors Affecting Adoption. *Sustainability*. https://doi.org/10.3390/su16072828.

Giua, C., Materia, V., & Camanzi, L. (2022). Smart farming technologies adoption: Which factors play a role in the digital transition?. *Technology in Society*. https://doi.org/10.1016/j.techsoc.2022.101869.

Javaid, M., Haleem, A., Khan, I., & Suman, R. (2022). Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochem*. https://doi.org/10.1016/j.aac.2022.10.001.

Jimma, T., Abera, W., Demissie, T., Spillane, C., Ture, K., Solomon, D., & Chemura, A. (2024). Quantifying Residual Soil Moisture through Empirical Orthogonal Functions Analysis to Support Legume-Based Cropping Systems. *Earth Systems and Environment.* https://doi.org/10.1007/s41748-024-00514-w.

Kangogo, D., Dentoni, D., & Bijman, J. (2020). Determinants of Farm Resilience to Climate Change: The Role of Farmer Entrepreneurship and Value Chain Collaborations. *Sustainability*. https://doi.org/10.3390/su12030868.

Khaliq, A., Khan, A., Jan, S., Umair, M., Gulshair, A., Ali, A., & Shah, U. (2025). AI-Driven Smart Agriculture: An Integrated Approach for Soil Analysis, Irrigation, and Crop-Fertilizer Recommendations. *IEEE Access, 13*, 141124-141138. https://doi.org/10.1109/access.2025.3594162.

Lakhiar, I., Yan, H., Zhang, C., Wang, G., He, B., Hao, B., Han, Y., Wang, B., Bao, R., Syed, T., Chauhdary, J., & Rakibuzzaman, M. (2024). A Review of Precision Irrigation Water-Saving Technology under Changing Climate for Enhancing Water Use Efficiency, Crop Yield, and Environmental Footprints. *Agriculture*. https://doi.org/10.3390/agriculture14071141.

Li, J., Liu, G., Chen, Y., & Li, R. (2023). Study on the influence mechanism of adoption of smart agriculture technology behavior. *Scientific Reports, 13*. https://doi.org/10.1038/s41598-023-35091-x.

Li, M., Xu, Y., Fu, Q., Singh, V., Singh, V., Liu, D., & Li, T. (2020). Efficient irrigation water allocation and its impact on agricultural sustainability and water scarcity under uncertainty. *Journal of Hydrology, 586,* 124888. https://doi.org/10.1016/j.jhydrol.2020.124888.

Ma, W., & Rahut, D. (2024). Climate-smart agriculture: adoption, impacts, and implications for sustainable development. *Mitigation and Adaptation Strategies for Global Change.* https://doi.org/10.1007/s11027-024-10139-z.

Malatji, W., Eck, R., & Zuva, T. (2020). Understanding the usage, Modifications, Limitations and Criticisms of Technology Acceptance

Model (TAM). Advances in Science, *Technology and Engineering Systems Journal, 5*, 113-117. https://doi.org/10.25046/aj050612.

Mallareddy, M., Thirumalaikumar, R., Balasubramanian, P., Naseeruddin, R., Nithya, N., Mariadoss, A., Eazhilkrishna, N., Choudhary, A., Deiveegan, M., Subramanian, E., Padmaja, B., & Vijayakumar, S. (2023). Maximizing Water Use Efficiency in Rice Farming: A Comprehensive Review of Innovative Irrigation Management Technologies. *Water*. https://doi.org/10.3390/w15101802.

Martínez-Dalmau, J., Gutiérrez-Martín, C., Kahil, T., & Berbel, J. (2023). Impact of alternative water policies for drought adaptation in the Guadalquivir Mediterranean river basin, southern Spain. *Journal of Hydrology: Regional Studies*. https://doi.org/10.1016/j.ejrh.2023.101444.

Meuwissen, M., Feindt, P., Spiegel, A., Termeer, C., Mathijs, E., Mey, Y., Finger, R., Balmann, A., Wauters, E., Urquhart, J., Vigani, M., Zawalińska, K., Herrera, H., Nicholas-Davies, P., Hansson, H., Paas, W., Slijper, T., Coopmans, I., Vroege, W., Ciechomska, A., Accatino, F., Kopainsky, B., Poortvliet, P., Candel, J., Maye, D., Severini, S., Senni, S., Soriano, B., Lagerkvist, C., Peneva, M., Gavrilescu, C., & Reidsma, P. (2019). A framework to assess the resilience of farming systems. *Agricultural Systems*. https://doi.org/10.1016/j.agsy.2019.102656.

Mishra, N., Bhandari, N., Maraseni, T., Devkota, N., Khanal, G., Bhusal, B., Basyal, D., Paudel, U., & Danuwar, R. (2024). Technology in farming: Unleashing farmers' behavioral intention for the adoption of agriculture 5.0. *PLOS ONE, 19*. https://doi.org/10.1371/journal.pone.0308883.

Mogaji, E., Viglia, G., Srivastava, P., & Dwivedi, Y. (2024). Is it the end of the technology acceptance model in the era of generative artificial intelligence?. *International Journal of Contemporary Hospitality Management*. https://doi.org/10.1108/ijchm-08-2023-1271.

Na, S., Heo, S., Han, S., Shin, Y., & Roh, Y. (2022). Acceptance Model of Artificial Intelligence (AI)-Based Technologies in Construction Firms: Applying the Technology Acceptance Model (TAM) in Combination with the Technology–Organisation–Environment (TOE) Framework. *Buildings*. https://doi.org/10.3390/buildings12020090.

Nautiyal, M., Joshi, S., Hussain, I., Rawat, H., Joshi, A., Saini, A., Kapoor, R., Verma, H., Nautiyal, A., Chikara, A., Ahmad, W., & Kumar, S. (2025). Revolutionizing agriculture: A comprehensive review on artificial intelligence applications in enhancing properties of agricultural produce. *Food Chemistry: X, 29*. https://doi.org/10.1016/j.fochx.2025.102748.

Niu, L., Qin, W., You, Y., Mo, Q., Pan, J., Tian, L., Xu, G., Chen, C., & Li, Z. (2023). Effects of precipitation variability and conservation tillage on soil moisture, yield and quality of silage maize. *Frontiers in Sustainable Food Systems*. https://doi.org/10.3389/fsufs.2023.1198649.

Nsoh, B., Katimbo, A., Guo, H., Heeren, D., Nakabuye, H., Qiao, X., Ge, Y., Rudnick, D., Wanyama, J., Bwambale, E., & Kiraga, S. (2024). Internet of Things-Based Automated Solutions Utilizing Machine Learning for Smart and Real-Time Irrigation Management: A Review. *Sensors (Basel, Switzerland), 24*. https://doi.org/10.3390/s24237480.

Olawumi, A., Oyediji, B., Bamidele, J., Eleke, U., Olaitan, M., & Sennuga, S. (2025). Artificial Intelligence in Agricultural Extension for Sustainable Livelihoods among Rural Farmers in Abuja, Nigeria. *Global Academic Journal of Agriculture and Biosciences*. https://doi.org/10.36348/gajab.2025.v07i03.002.

Peladarinos, N., Piromalis, D., Cheimaras, V., Tserepas, E., Munteanu, R., & Papageorgas, P. (2023). Enhancing Smart Agriculture by Implementing Digital Twins: A Comprehensive Review. *Sensors (Basel, Switzerland), 23*. https://doi.org/10.3390/s23167128.

Qiao, L., Wang, X., Smith, P., Fan, J., Lu, Y., Emmett, B., Li, R., Dorling, S., Chen, H., Liu, S., Benton, T., Wang, Y., , Y., Jiang, R., Zhang, F., Piao, S., Müller, C., Yang, H., Hao, Y., Li, W., & Fan, M. (2022). Soil quality both increases crop production and improves resilience to climate change. *Nature Climate Change, 12*, 574 - 580. https://doi.org/10.1038/s41558-022-01376-8.

Rahimi, B., Nadri, H., Afshar, H., & Timpka, T. (2018). A Systematic Review of the Technology Acceptance Model in Health Informatics. *Applied Clinical Informatics, 09*, 604 - 634. https://doi.org/10.1055/s-0038-1668091.

Ross, A., Connolly, K., Vögele, S., & Kuckshinrichs, W. (2024). A macro-level analysis of the socio-economic impacts of climate change driven water scarcity: Incorporating behavioural and resilience aspects. *Water Research X, 23*. https://doi.org/10.1016/j.wroa.2024.100223.

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128*, 13-35. https://doi.org/10.1016/j.compedu.2018.09.009.

Sharma, R., Rallapalli, S., & Magner, J. (2025). Optimizing water-efficient agriculture: evaluating the sustainability of soil management and irrigation synergies using fuzzy extent analysis. *Scientific Reports, 15*. https://doi.org/10.1038/s41598-025-15426-6.

Sharma, S., Bennett, M., & Mehra, P. (2025). Roles of hormones in regulating root growth–water interactions. *Journal of Experimental Botany, 76*, 1987 - 1995. https://doi.org/10.1093/jxb/eraf063.

Stone, J., & Rahimifard, S. (2018). Resilience in agri-food supply chains: a critical analysis of the literature and synthesis of a novel framework. *Supply Chain Management, 23*, 207-238. https://doi.org/10.1108/scm-06-2017-0201.

Stuecker, M., Tigchelaar, M., & Kantar, M. (2018). Climate variability impacts on rice production in the Philippines. *PLoS ONE, 13*. https://doi.org/10.1371/journal.pone.0201426.

Sutcliffe, C., Knox, J., & Hess, T. (2021). Managing irrigation under pressure: How supply chain demands and environmental objectives drive imbalance in agricultural resilience to water shortages. *Agricultural Water Management, 243*, 106484. https://doi.org/10.1016/j.agwat.2020.106484.

T, M. (2025). Adoption and Usage of New Technologies in Farming: A Study Farmer's in Coimbatore City. *International Journal For Multidisciplinary Research*. https://doi.org/10.36948/ijfmr.2025.v07i02.40276.

Usigbe, M., Asem-Hiablie, S., Uyeh, D., Iyiola, O., Park, T., & Mallipeddi, R. (2023). Enhancing resilience in agricultural production systems with AI-based technologies. *Environment, Development and Sustainability*, 1-29. https://doi.org/10.1007/s10668-023-03588-0.

Vallejo-Gómez, D., Osorio, M., & Hincapié, C. (2023). Smart Irrigation Systems in Agriculture: A Systematic Review. *Agronomy*. https://doi.org/10.3390/agronomy13020342.

Vennam, R., Ramamoorthy, P., Poudel, S., Reddy, K., Henry, W., & Bheemanahalli, R. (2023). Developing Functional Relationships between Soil Moisture Content and Corn Early-Season Physiology, Growth, and Development. *Plants, 12*. https://doi.org/10.3390/plants12132471.

Yang, M., Wang, G., Lazin, R., Shen, X., & Anagnostou, E. (2021). Impact of planting time soil moisture on cereal crop yield in the Upper Blue Nile Basin: A novel insight towards agricultural water management. *Agricultural Water Management, 243*, 106430. https://doi.org/10.1016/j.agwat.2020.106430.

Zidan, F., & Febriyanti, D. (2024). Optimizing Agricultural Yields with Artificial Intelligence-Based Climate Adaptation Strategies. *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*. https://doi.org/10.34306/itsdi.v5i2.663.