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Beyond Efficiency: Smart Farming, Climate Change, and the Resilience of Food Crop Productivity

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Abstract
Purpose: This study aims to examine the effect of smart farming implementation on food crop productivity in Indonesia and analyze the moderating role of climate change on this relationship.
Research Methodology: This study used a quantitative cross-sectional survey design conducted among food crop farmers in Indonesia. Data were collected using a structured questionnaire with a five-point Likert scale. Purposive sampling was applied to 200 respondents. The analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software to test reliability, validity, and hypothesis relationships.
Results: The findings show that the implementation of smart farming positively influences crop productivity. Climate change significantly affects crop productivity. Furthermore, climate change strengthens the relationship between smart farming and crop productivity.
Conclusions: Write the main conclusions of the research. Smart farming plays an important role in improving food crop productivity, especially under increasing climate-change pressures.
Limitations: This study relied on self-reported survey data and used a cross-sectional design, limiting long-term causal interpretation.
Contributions: This study contributes to digital agriculture and climate adaptation research by providing empirical evidence of the role of smart farming in improving productivity and resilience, supporting policymakers and farmers in developing climate-smart agricultural strategies.

Keywords: *Climate Change, Crop Productivity, Smart Farming, Sustainable Agriculture, Technology Adoption*

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1. Introduction

The agricultural sector plays a fundamental role in ensuring global food security and economic stability. However, rapid population growth, diminishing arable land, and changing climate patterns have significantly challenged traditional farming systems. Climate change, characterized by increasing temperatures, altered precipitation regimes, and more frequent extreme weather events, is projected to reduce global crop yields by up to 10–20 %, posing a direct threat to food availability and livelihoods, particularly in developing regions (Begna & Wakweya, 2025).

Simultaneously, the integration of digital technologies within agriculture, often termed smart farming, has gained momentum as a strategic solution to these challenges. Smart farming leverages the Internet of Things (IoT), Artificial Intelligence (AI), sensor networks, and data analytics to optimize resource use, enhance monitoring capabilities, and improve decision-making- in cultivation practices, leading to improved crop productivity and resource efficiency (Choudhary, Guha, Pau, & Mishra, 2025).

These global trends are also reflected in the context of developing agricultural economies, such as Indonesia, where climate variability has increasingly disrupted staple crop production, such as rice, maize, and horticultural commodities. Farmers often face unpredictable rainfall patterns, rising temperatures, and soil moisture stress, which contribute to yield instability and increase the vulnerability of smallholder producers (Mohamed et al., 2021). Despite the promise of smart farming technologies, their adoption remains uneven, with barriers such as limited digital literacy, high initial costs, and infrastructural constraints in rural areas. For instance, while IoT-based- systems can enhance precision irrigation and reduce input waste, many agrarian communities in regions such as Central Java, West Java, and Sulawesi have yet to fully integrate these technologies into mainstream practice.

This disparity highlights a critical challenge: while smart farming has been demonstrated to increase crop yields and efficiency in certain pilot contexts, its impact across broader geographic and socio-economic landscapes has not been fully quantified. Moreover, research on how smart farming interacts with climate change, whether as a buffer, enhancer, or neutral factor in productivity outcomes, remains limited (Piancharoenwong & Badir, 2024). Theoretically, this study is grounded in the Diffusion of Innovations Theory (DOI) and Technology Acceptance Model (TAM), which suggest that the adoption of technological innovations is influenced by perceived benefits, compatibility with existing practices, and environmental pressures. These frameworks help explain why smart farming may be adopted in some agricultural contexts but resisted in others, particularly where climatic stress is pronounced and resources are limited.

Previous empirical research has explored the components of this problem. For example, studies have shown that IoT-based systems can improve crop monitoring and boost yields under controlled conditions (Shahab, Naeem, Iqbal, Aqeel, & Ullah, 2025). Others have highlighted the potential of AI-assisted- climate adaptation strategies to optimize agricultural outputs under variable conditions (Hermanus, 2022). There is a need for resilient farming practices to mitigate the impacts of climate stress on food production (Konfo et al., 2024).

However, gaps remain in the few quantitative studies that directly measure the impact of smart farming adoption on actual crop productivity metrics in climate-stressed- environments. Limited research has incorporated the moderating effects of climate change variables (e.g., temperature variability and rainfall anomalies) on the relationship between smart farming and productivity. Most existing studies focus on pilot technologies rather than systemic implementation at the farm or district level. There is a lack of region-specific- empirical evidence from nations with agrarian-based- economies, such as Indonesia (Riadi, Rohmah Nurazizah, Wakano, & Fadilah, 2023).

Based on the identified gaps, the novelty of this study lies in three main aspects. First, this study integrates the implementation of smart farming with the moderation of climate change, unlike previous studies that examined smart farming or climate-smart agriculture separately. This study quantitatively investigates how smart farming interacts with climate change variables, such as temperature anomalies and rainfall variability, in influencing crop productivity, providing a deeper understanding of the effectiveness of technology under real environmental stress (Marhaen, Kusmiadi, & Ropalia, 2023).

Second, this study presents empirical evidence from a region-specific context, namely Indonesia, an agrarian country highly vulnerable to climate variability, thereby addressing the lack of localized quantitative data, in contrast to prior studies that focused largely on pilot projects or developed countries (Nurhaedah, Irmayani, Ruslang, & Jumrah, 2023). Third, this study employs a comprehensive measurement of productivity, including yield per hectare, growth parameters, and crop quality, combined with the level of smart farming technology adoption, ensuring that both efficiency and output quality are captured thoroughly. By emphasizing these aspects, this research not only fills a scientific gap but also produces findings that can be practically applied by policymakers, agricultural extension services, and farmers, thereby supporting evidence-based strategies for technology and climate adaptation (Ramlan, Irmayani, & Nurhaeda, 2023).

This study contributes to the empirical literature on digital agriculture and offers practical insights for policymakers, agricultural extension services, and farming communities. An improved understanding in this area could aid in designing targeted interventions to scale technology adoption, enhance climate resilience, and support sustainable food systems (Yudhistira, Suprapto, & Sulmartiwi, 2023). In summary, this study seeks to answer the following question: How does the implementation of smart farming technologies influence crop productivity under varying levels of climate-change exposure? The findings aim to contribute both practically, by informing agricultural strategy and technology deployment, and theoretically, by elucidating the interactive dynamics between technological innovation and environmental stress in agricultural contexts.

2. Literature Review and Hypotheses Development

2.1 Smart Farming Implementation and Crop Productivity

Smart farming refers to the application of advanced digital technologies, such as the Internet of Things (IoT), sensors, Artificial Intelligence (AI), and data analytics, to optimize agricultural systems and improve decision-making- processes in crop production (Santoso, Hani, & Putra, 2022). Previous research indicates that smart farming technologies can enhance resource-use efficiency, real-time- monitoring, and automated farm management, which collectively contribute to higher crop productivity and sustainable agricultural outcomes (Yudhistira et al., 2023). For example, modern IoT-based systems have been shown to enable precision irrigation and input optimization, thereby reducing waste and improving yield results under diverse environmental conditions (Ali, Hussain, Tantashutikun, Hussain, & Cocetta, 2023; Padmanabha, Kobelski, Hempel, & Streif, 2023).

Empirical evidence further suggests that the adoption of smart farming practices correlates with increased agricultural output at the farm level (Junistia, Nearti, & Jayanti, 2025). Quantitative analysis from large-scale databases in Thailand demonstrated that smart farming initiatives under national digital transformation strategies significantly improved total factor productivity in agricultural production (Hwang, Jitanugoon, & Puntha, 2024).

However, the magnitude and consistency of these productivity gains vary widely across geographic contexts, crop types, and technology intensities (Irmayani, Adnin, & Irwan, 2025). Some studies argue that despite the theoretical potential of smart farming technologies, actual yield improvements remain under-realized- owing to infrastructural limitations, lack of digital skills among farmers, and high adoption costs, especially in developing economies. Accordingly, higher levels of smart farming implementation are expected to be associated with improved crop productivity outcomes.

H_1**:** Smart farming implementation has a positive and significant effect on crop productivity

2.2 The Moderating Role of Climate Change on Smart Farming and Productivity

Climate change is widely recognized as a major threat to global agricultural productivity. Systematic literature reviews show that without adequate adaptation strategies, changes in temperature, precipitation patterns, and extreme weather events are projected to decrease food production by up to 14% globally by mid-century-, even as demand for food increases (Farah et al., 2025). Despite the potential of adaptation practices, such as Climate-Smart- Agriculture (CSA), to mitigate adverse effects and improve productivity, the evidence remains mixed and context-dependent (Frija, 2024). Some empirical research has found that climate-smart- agricultural practices can enhance crop yields and income among smallholder farmers facing climatic stress, suggesting a possible moderating effect of adaptation strategies on productivity outcomes under climate variability (Mpinda, Bett, & Muluvi, 2025).

Smart farming technologies can be considered a subset of CSA innovation, offering real-time- environmental monitoring, predictive analytics, and precise resource management that may cushion the negative impacts of climate change on crop performance (Wei, 2023). For instance, IoT sensors and weather forecasts can help farmers apply water and nutrients more efficiently during droughts or heat stress (Dhanaraju, Chenniappan, Ramalingam, Pazhanivelan, & Kaliaperumal, 2022).

However, research exploring the interaction effect between smart farming implementation and climate change impact on crop productivity is still sparse, especially in empirically quantifying how climatic variability conditions, such as rainfall anomalies or temperature extremes, influence the effectiveness of smart farming on yield (Nasihin et al., 2025). This gap suggests that the strength of the relationship between smart farming and crop productivity may be conditioned by the intensity of climate change (Lu, Zhang, Fang, Ke, & Yang, 2017). Thus, the hypothesize is

H_2**:** Climate change moderates the relationship between smart farming implementation and crop productivity, such that the positive effect of smart farming implementation on crop productivity is stronger (or weaker) under specific climate change conditions

2.3 Climate Change and Crop Productivity

Climate change has been widely acknowledged as a critical factor influencing agricultural productivity (Geetika et al., 2022). Rising temperatures, erratic rainfall patterns, and more frequent extreme weather events can directly affect crop growth, yields, and quality (Kamilaris & Prenafeta-Boldú, 2018). Studies have shown that climate variability often leads to decreased agricultural output, particularly in regions with rain-fed agriculture and smallholder farming systems. Empirical research indicates that higher temperatures and irregular rainfall negatively impact the physiological processes of crops, reduce soil fertility, and increase their vulnerability to pests and diseases (Y. Xu & Xu, 2022). For instance, rice and maize yields in tropical regions have significantly declined under prolonged heat stress and drought conditions.

From a theoretical perspective, climate change acts as an environmental stressor in agricultural production systems (Oppon, Richter, Koh, & Nabayiga, 2023). According to the Resilience Theory in agroecosystems, exposure to climatic stress without proper adaptation mechanisms can reduce productivity and system stability (Wolfert, Ge, Verdouw, & Bogaardt, 2017). Therefore, the following hypothesis is proposed:

H3: Climate change has a negative and significant effect on crop productivity

2.4 Supporting Theoretical and Empirical Foundations

The Diffusion of Innovations Theory (DOI) and Technology Acceptance Model (TAM) provide a theoretical basis for the adoption and impact of smart farming technologies (C. Xu, He, Chen, & Hu, 2023). The DOI suggests that the rate and success of technology adoption depend on perceived relative advantage, compatibility with existing systems, and observability of results, all of which influence how readily farmers implement smart farming practices (Fumagalli & Martin, 2023). TAM posits that perceived usefulness and ease of use shape attitudes toward new technologies, influencing actual adoption behaviors.

These frameworks support the expectation that smart farming's potential for increasing productivity will be realized only if farmers perceive its benefits and can effectively integrate it into their operations and management. Empirical studies also suggest that climate change adaptation practices, such as CSA, enhance crop resilience and productivity under environmental stress, pointing to the plausibility of climate factors altering the productivity benefits of technological interventions.

2.5 Summary of Literature Gaps

While substantial literature exists on the potential of smart farming to improve agricultural productivity and on climate change impacts on agriculture, very few studies have explicitly tested the interactive effects between smart farming implementation and climate change variables on crop productivity using quantitative models. Furthermore, most available evidence is limited to case studies or pilot projects rather than systematic empirical analyses at broader farm or regional levels.

This study aims to fill this gap by:

1. quantitatively measuring the effect of smart farming implementation on crop productivity,
2. integrating climate change conditions as a moderating variable, and
3. providing region-specific- evidence from the context of a developing agricultural economy.

The figure below illustrates the conceptual framework of this study, highlighting the proposed relationships among the variables and the mediating and moderating mechanisms incorporated in the research design.

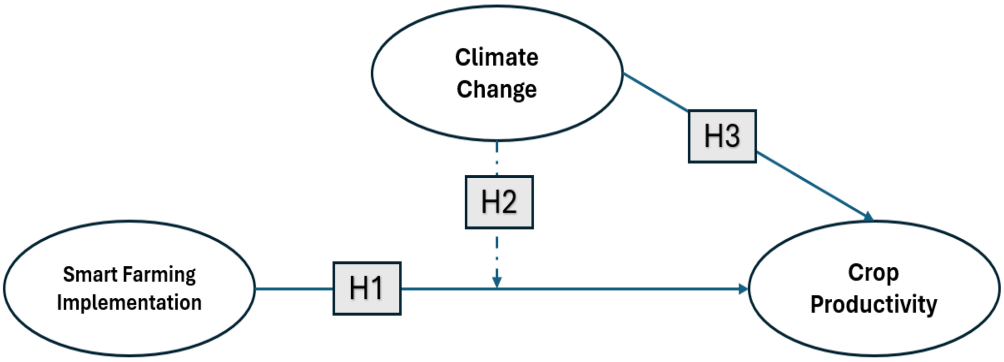

Figure 1. Conceptual framework

3. Methodology

3.1 Research Design

This study adopted a quantitative cross-sectional survey design, which is widely accepted in research that examines relationships between variables at a single point in time to test hypotheses and estimate associations efficiently across a large sample. Such designs have been used in agricultural and social science research to evaluate the determinants of behavior or technology adoption using structured questionnaires and statistical modeling techniques (Hair, Sarstedt, Pieper, & Ringle, 2012). The cross-sectional approach allows for the efficient collection of data from a large sample at a single point in time, thereby facilitating the examination of direct effects (e.g., smart farming on crop productivity) and conditional effects (moderation by climate change) within the research model.

PLS-SEM is a recognized analytical tool for complex multivariate models involving latent constructs and moderation effects in quantitative research designs, particularly when the research objective is to predict and explain variance in dependent variables. Approaches similar to this have been applied in agricultural studies that assess the impacts of digital technology and environmental adaptation, where structured surveys are used alongside SEM to empirically assess relationships among constructs (Bocean, 2024).

3.2 Population and Sample

A purposive sampling technique was employed to ensure that the participants had relevant farming experience and familiarity with smart farming practices. Purposive sampling is suitable when researchers seek respondents with specific characteristics that are integral to the research questions, such as technology use in agriculture. To determine the appropriate sample size for PLS-SEM, this study adopts guideline heuristics that recommend minimum sample thresholds based on either the number of indicators or model complexity.

According to the commonly cited 10-times rule and related guidelines, the minimum sample size should be 5–10 times the maximum number of structural paths or indicators in the model to achieve stable parameter estimates (Kock & Hadaya, 2018). Given that the model has 12 observed indicators across all constructs, the estimated minimum sample requirement would be.

$$Nmin = 12x5 = 60 \tag{1}$$

The upper threshold for model stability is:

$$Nmax = 12x10 = 120 \quad (2)$$

To ensure sufficient statistical power for moderation analysis and reliable bootstrapping results, the target sample size was increased beyond these heuristics, resulting in a final sample exceeding 200 respondents, in line with PLS-SEM research that suggests larger samples improve power and the stability of SEM estimates (Memon et al., 2020).

3.3 Instruments and Measurement Scale

Data were collected using a structured questionnaire consisting of reflective measurement scales for all constructs.

1. Smart Farming Implementation (*X*): indicators included the use of soil moisture sensors, automated irrigation, digital monitoring apps, and technology-assisted pest/disease detection, which are typical components of smart farming systems described in the literature on IoT and precision agriculture.
2. Crop Productivity (*Y*): measured via yield per hectare, plant growth parameters, and crop quality indicators, which align with operational productivity metrics used in agricultural technology studies.
3. Climate Change (*M*): measured using indicators such as temperature variability, rainfall anomalies, frequency of extreme weather events, and humidity/drought occurrences, reflecting the typical environmental variables considered in climate-impact research.

Each item utilized a five-point Likert scale or ratio scale as appropriate (i.e., 1 = strongly disagree/very low to 5 = strongly agree/very high for perceptual items), consistent with the quantitative survey instruments used in SEM research.

Table 1. Summary of variables and indicators

Variables	Indicators (Short Items)	Source
X – Smart Farming Implementation	1. Use of soil moisture sensors 2. Automated irrigation systems 3. Digital crop monitoring apps 4. Technology-assisted pest/disease detection	Literature on IoT & smart agriculture implementation (Ali et al., 2023)
Y – Crop Productivity	1. Crop yield per hectare 2. Avg. plant height and leaf count 3. Crop quality	Empirical agriculture productivity measures (Begna & Wakweya, 2025)
M – Climate Change	1. Avg. temperature anomaly 2. Rainfall variability 3. Extreme weather frequency 4. Humidity fluctuations 5. Drought/flood occurrence	Climate variability indicators in agriculture contexts

3.4 Data Analysis Technique

3.4.1 Descriptive Statistics

Descriptive statistics were conducted to summarize respondents' demographic profiles (age, gender, farm size, and education) and distributions of survey responses as a standard first step in quantitative analysis for understanding sample characteristics.

3.4.2 Partial Least Squares Structural Equation Modeling (PLS-SEM)

Inferential analyses were carried out using Partial Least Squares Structural Equation Modeling (PLS-SEM), a variance-based SEM approach suitable for predictive models, latent constructs, and moderation effects. PLS-SEM is commonly used when data do not strictly meet normal distribution assumptions and when the research focus involves explaining the variance in endogenous variables.

3.4.2.1 Measurement Model Evaluation

1. Convergent validity: indicator loadings ≥ 0.70; AVE ≥ 0.50.
2. Construct reliability: composite reliability ≥ 0.70; Cronbach's alpha ≥ 0.70.
3. Discriminant validity: Fornell–Larcker and Heterotrait-Monotrait (HTMT) criteria.

3.4.2.2 Structural Model Assessment

1. R^2 to quantify the explained variance in crop productivity.
2. Effect size (f^2) was used to assess individual predictor contributions.
3. Bootstrapping with 5,000 resamples for significance testing (t-statistics and p-values).
4. Moderation analysis using interaction terms (Smart Farming × Climate Change) via product indicators or two-stage approaches in PLS-SEM.

These evaluation criteria and techniques represent widely accepted PLS-SEM practices for robust modeling of moderation effects in quantitative research

4. Results and Discussions

4.1 Results

4.1.1 Descriptive Statistics of Respondents

This section presents the respondents' descriptive statistics to provide an overview of their demographic characteristics. The analysis includes key respondent profiles, such as gender, age, education level, type of crop cultivated, farm size, farming experience, smart farming tool usage, and monthly farming income. These descriptive results are important for understanding the sample composition and ensuring that the respondents represent the target population of this study.

Table 2. Demographic profile of respondents (N = 200)

Demographic Variables	Category	Frequency (n)	Percentage (%)
Gender	Male	148	74.0
	Female	52	26.0
Age	18–25 years	18	9.0
	26–35 years	54	27.0
	36–45 years	66	33.0
	46–55 years	42	21.0
	>55 years	20	10.0
Education Level	Elementary School	36	18.0
	Junior High School	52	26.0
	Senior High School	74	37.0
	Diploma (D1–D3)	22	11.0
	Bachelor Degree or higher	16	8.0
Type of Crop Cultivated	Rice	92	46.0
	Maize	48	24.0
	Horticulture	60	30.0
Farm Size	< 1 hectare	58	29.0
	1–2 hectares	82	41.0
	2.1–5 hectares	46	23.0
	> 5 hectares	14	7.0
Farming Experience	< 5 years	22	11.0
	5–10 years	54	27.0
	11–20 years	76	38.0
	> 20 years	48	24.0
Smart Farming Tool Usage	Yes	126	63.0
	No	74	37.0
Monthly Farming Income	< IDR 2,000,000	44	22.0
	IDR 2,000,000–4,000,000	86	43.0
	IDR 4,000,000–6,000,000	48	24.0
	> IDR 6,000,000	22	11.0

Based on Table 2, which the data are collected from 200 respondents, the majority of participants were male farmers, accounting for 148 respondents (74%), while female farmers represented 52 respondents (26%). This indicates that farming activities within the observed population are predominantly managed by men, although female participation remains notable. In terms of age distribution, most respondents were in the productive working age group. The largest proportion came from the 36–45 years category with 66 respondents (33%), followed by the 26–35 years with 54 respondents (27%), and the 46–55 years with 42 respondents (21%). Meanwhile, younger farmers aged 18–25 years accounted for only 9%, and respondents aged above 55 years represented 10%. This suggests that farming is largely dominated by middle-aged individuals, which may influence their willingness and capability to adopt smart farming technologies.

Regarding education level, the highest number of respondents had completed senior high school, totalling 74 (37%). This was followed by junior high school graduates (26 %) and elementary school graduates (18 %). Respondents with higher education were relatively limited, with 11% holding diplomas and only 8% holding bachelor's degrees or higher. This implies that the general educational background of farmers remains moderate, which may affect their technological literacy and ability to understand digital farming.

Based on crop type, nearly half of the respondents were rice farmers, consisting of 92 respondents (46%), while horticultural farmers represented 60 respondents (30%), and maize farmers represented 48 respondents (24%). This indicates that rice remains the dominant staple crop among the respondents, reflecting Indonesia's reliance on rice production as a key agricultural commodity. In terms of farm size, most respondents managed relatively small-scale farms. The majority owned or managed 1–2 hectares of land (82 respondents, 41%), followed by farmers with land sizes below 1 ha (58 respondents, 29%). Farmers with land sizes between 2.1 and 5 hectares represented 23%, while only 7% cultivated land larger than 5 hectares. These results suggest that the sample mainly represents small- and medium-scale farmers, which is typical of Indonesian agricultural settings.

The farming experience profile showed that most respondents were experienced farmers. Respondents with 11–20 years of experience comprised the largest group (76 respondents, 38%), followed by those with more than 20 years (48 respondents, 24%) and 5–10 years (54 respondents, 27%). Only 11% had less than five years of experience. This indicates that most participants possessed substantial farming knowledge, which may have strengthened the reliability of their responses related to productivity and climate impacts. Furthermore, regarding the adoption of smart farming tools, 126 respondents (63%) reported using smart farming technologies, whereas 74 respondents (37%) indicated that they had not adopted such tools. This suggests that smart farming adoption is relatively high within the sample, providing sufficient variation to test the influence of smart farming implementation on the productivity.

Finally, in terms of monthly farming income, the largest portion of respondents earned IDR 2,000,000–4,000,000 per month (86 respondents, 43%), followed by those earning IDR 4,000,000–6,000,000 per month (48 respondents, 24%). Respondents earning less than IDR 2,000,000 accounted for 22%, while only 11% earned above IDR 6,000,000. This indicates that most respondents fall into the middle-income farming group, reflecting the economic conditions of the smallholder farmers. Overall, the demographic characteristics show that the respondents were mostly middle-aged male farmers with moderate education levels, relatively small farm sizes, and considerable experience. These characteristics are relevant to the research context because they influence the capacity and readiness of farmers to adopt smart farming practices under climate change conditions.

4.2 Outer Model

4.2.1 Outer Loading

This section presents the outer loading results to evaluate the indicator reliability of each construct in the measurement model. Outer loadings were examined to determine the extent to which each indicator appropriately represents its latent variable, where values above 0.70 indicate that the indicators have strong contributions and are considered valid for further analysis.

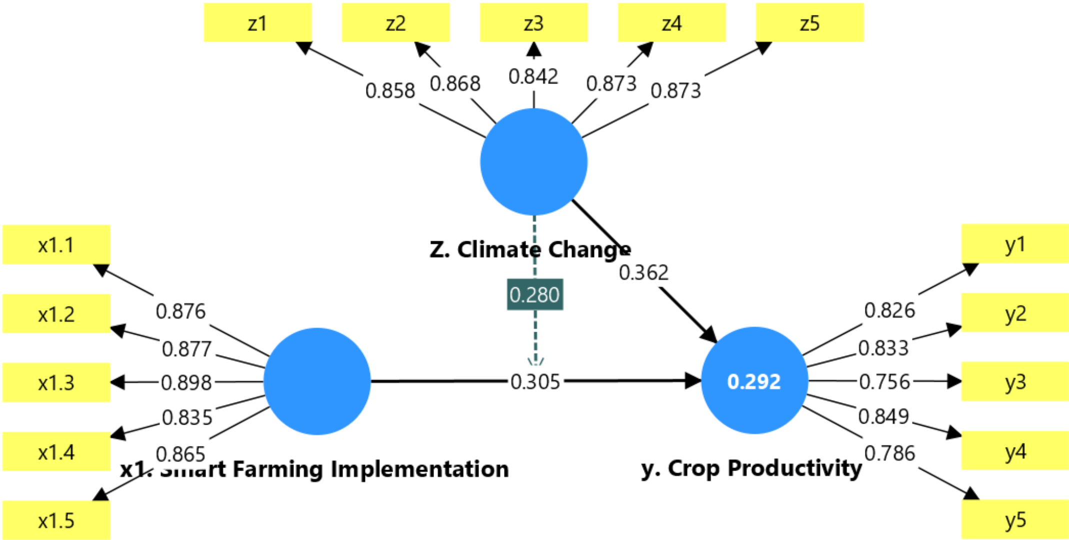

Figure 2. Outer loadings diagram

The results of the PLS-SEM model indicate that all constructs in this study meet the required measurement quality, as reflected by the outer loading value. The indicators of Smart Farming Implementation showed strong loadings ranging from 0.835 to 0.898, while Climate Change indicators ranged from 0.842 to 0.873, and Crop Productivity indicators ranged from 0.756 to 0.849. Since all values exceeded the minimum threshold of 0.70, the indicators were considered valid and reliable in representing their respective latent variables. In the structural model, Smart Farming implementation had a positive effect on Crop Productivity ($\beta = 0.305$), indicating that higher adoption of smart farming technologies, such as automated irrigation, digital monitoring, and pest detection systems, contributes to improved agricultural productivity.

Climate Change also has a direct influence on Crop Productivity ($\beta = 0.362$), suggesting that climate variability significantly affects farming outcomes. Importantly, the moderating effect of Climate Change is positive ($\beta = 0.280$), indicating that climate change strengthens the relationship between smart farming and crop productivity. This implies that smart farming becomes more beneficial and critical under increasing climate pressures, as it helps farmers adapt to uncertain weather conditions and maintain their productivity levels.

Furthermore, the R-square value for Crop Productivity is 0.292, indicating that Smart Farming Implementation and Climate Change together explain 29.2% of the variance in crop productivity, while the remaining variance may be influenced by other factors such as soil quality, farming inputs, labor availability, and market access. Overall, these findings support the research objective that smart farming plays an important role in enhancing food crop productivity in the era of climate change. For future research, it is recommended to consider separating the dimensions of Climate Change (e.g., climate variability, extreme events, or adaptive pressure) or testing a second-order construct to capture its multi-faceted nature more accurately.

4.2.2 Construct Reliability and Validity – Overview

This subsection presents an overview of construct reliability and validity to ensure that all latent variables in the measurement model are measured accurately. The evaluation includes key criteria such as Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE), which are used to confirm internal consistency reliability and convergent validity before proceeding to the structural model assessment.

Table 3. Construct reliability and validity

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Z. Climate Change	0.915	0.920	0.936	0.745
X_1. Smart Farming Implementation	0.920	0.928	0.940	0.758
Y. Crop Productivity	0.871	0.889	0.905	0.657

Table 3 shows the construct reliability and validity results, indicating that all variables in the measurement model met the recommended thresholds. For climate change, Cronbach's alpha (0.915) and composite reliability values (rho_a = 0.920; rho_c = 0.936) were all above 0.70, confirming strong internal consistency reliability. Its AVE value of 0.745 also exceeds the minimum requirement of 0.50, indicating excellent convergent validity and that the construct explains a high proportion of variance in its indicators.

Similarly, Smart Farming demonstrated very high reliability, with a Cronbach's alpha of 0.920 and composite reliability values (rho_a = 0.928; rho_c = 0.940), suggesting that the indicators consistently measure the construct. The AVE value of 0.758 further confirmed strong convergent validity. For Crop Productivity, Cronbach's alpha (0.871) and composite reliability (rho_a = 0.889; rho_c = 0.905) also exceeded the acceptable level, indicating good reliability. The AVE value of 0.657 confirms that the construct has adequate convergent validity. Overall, these findings show that all constructs in the study are reliable and valid, indicating that the measurement model is statistically sound and suitable for further structural model evaluation.

4.2.3 Discriminant Validity (HTMT Matrix)

This subsection presents the results of the discriminant validity assessment using the Heterotrait–Monotrait Ratio (HTMT) matrix. The HTMT values were examined to confirm that each construct was empirically distinct from the others, ensuring that the indicators measured different concepts within the research model. Discriminant validity is considered satisfactory when the HTMT values are below the recommended threshold of 0.90.

Table 4. Discriminant validity

	***Z.* Climate Change**	**X_1. Smart Farming Implementation**	***Y.* Crop Productivity**	***Z.* Climate Change x X_1. Smart Farming Implementation**
Z. Climate Change				
X_1. Smart Farming Implementation	0.106			
Y. Crop Productivity	0.425	0.320		
Z. Climate Change x X_1. Smart Farming Implementation	0.022	0.152	0.251	

Table 4 shows that the HTMT matrix was used to assess discriminant validity, ensuring that the constructs of Climate Change, Smart Farming Implementation, Crop Productivity, and the interaction construct Climate Change × Smart Farming Implementation are truly distinct from each other. Discriminant validity is considered adequate if all HTMT values between constructs are below 0.90 (or, more strictly, below 0.85). If all values meet this threshold, it can be concluded that each variable in the research model measures a different concept and that there is no overlap between constructs.

Therefore, the measurement model in this study satisfies discriminant validity requirements and can proceed to the structural model analysis to examine the effect of smart farming on crop productivity and the moderating role of climate change. Theoretically, Climate Change is positioned as an external pressure because it represents an environmental factor that influences farming operations rather than merely serving as a contextual factor for smart farming implementation. This positioning is supported by risk management and agronomy literature, which emphasizes that climate change imposes adaptive pressures on farmers, making its interaction with smart farming critical for enhancing resilience and crop productivity.

4.3 Inner Model

4.3.1 R-Square

This section presents the evaluation of the inner (structural) model to examine the predictive power of the proposed framework. Specifically, the R-squared (R^2) values are reported to assess the extent to which the independent and moderating variables explain the variance in the endogenous construct, namely, Crop Productivity. Higher R^2 values indicate a stronger explanatory capability of the model.

Table 5. R-Square

	R-square	**R-square adjusted**
***Y*. Crop Productivity**	0.292	0.282

Table 5 shows that the R-squared results indicate that Crop Productivity has an R^2 value of 0.292 and an adjusted R^2 of 0.282. These values suggest that the independent variable SF-IM and the moderating variable Climate Change (including their interaction effect) together contribute to explaining 29.2% of the variance in crop productivity, while the remaining 70.8% is influenced by other factors not included in the model, such as soil quality, access to capital and inputs, farmers' human resource capacity, and institutional or market support. These variables were intentionally excluded to maintain the analytical focus. The adjusted R^2 value (0.282) was slightly lower than the R^2, indicating that the explanatory power remained relatively stable after accounting for the number of predictors.

Importantly, this model should be interpreted as a partial explanatory model rather than a comprehensive model of agricultural productivity. This reflects a technology-based adaptive approach to productivity under climate pressures, rather than claiming to determine agricultural outcomes as the sole driver. The moderate R^2 further emphasizes that crop productivity cannot be reduced to technology alone: smart farming acts as an adaptive enabler within a complex agricultural system, helping farmers cope with climate variability rather than serving as the singular determinant of productivity.

4.3.2 F-Square

This subsection presents the effect size (f^2) results to evaluate the relative contribution of each exogenous construct in explaining the variance of the endogenous variable, Crop Productivity. The f^2 values indicate whether Smart Farming Implementation, Climate Change, and their interaction term have a small, medium, or large impact on the structural model. According to commonly used guidelines, f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively, respectively.

Table 6. F-Square

	Z. Climate Change	**X_1. Smart Farming Implementation**	***Y*. Crop Productivity**	**Z. Climate Change x X_1. Smart Farming Implementation**
Z. Climate Change			0.183	
X_1. Smart Farming Implementation			0.128	

Y. Crop Productivity				
Z. Climate Change x X_1. Smart Farming Implementation			0.097	

Table 6 shows the f-square (f^2) results, indicating the relative effect size of each predictor on the endogenous variable, Crop Productivity. The construct Climate Change showed an f^2 value of 0.183, which falls within the medium effect size category, suggesting that climate-related factors act as a dominant external pressure influencing variations in crop productivity. Meanwhile, Smart Farming Implementation has an f^2 value of 0.128, indicating a small to moderate effect, meaning that the adoption of smart farming technologies serves as an adaptive and mitigating mechanism to cope with climate pressures, rather than replacing other agro-ecological factors.

Furthermore, the interaction term between Climate Change and Smart Farming Implementation has an f^2 value of 0.097, which represents a small effect size, implying that the moderating role of climate change contributes a relatively limited additional explanatory power to crop productivity. Overall, these findings reinforce that climate change is the primary external driver in the model, smart farming functions as an adaptive enabler, and the moderation effect provides a smaller yet relevant influence on strengthening the relationship between smart farming practices and crop productivity.

4.3.3 Hypothesis Result

This subsection presents the hypothesis testing results based on the structural model analysis using the bootstrapping method. The results include path coefficients, t-statistics, and p-values to determine whether the proposed hypotheses are supported or not. This analysis was conducted to examine the direct effects of Smart Farming Implementation and Climate Change on Crop Productivity, as well as the moderating effect of Climate Change on the relationship between smart farming implementation and crop productivity.

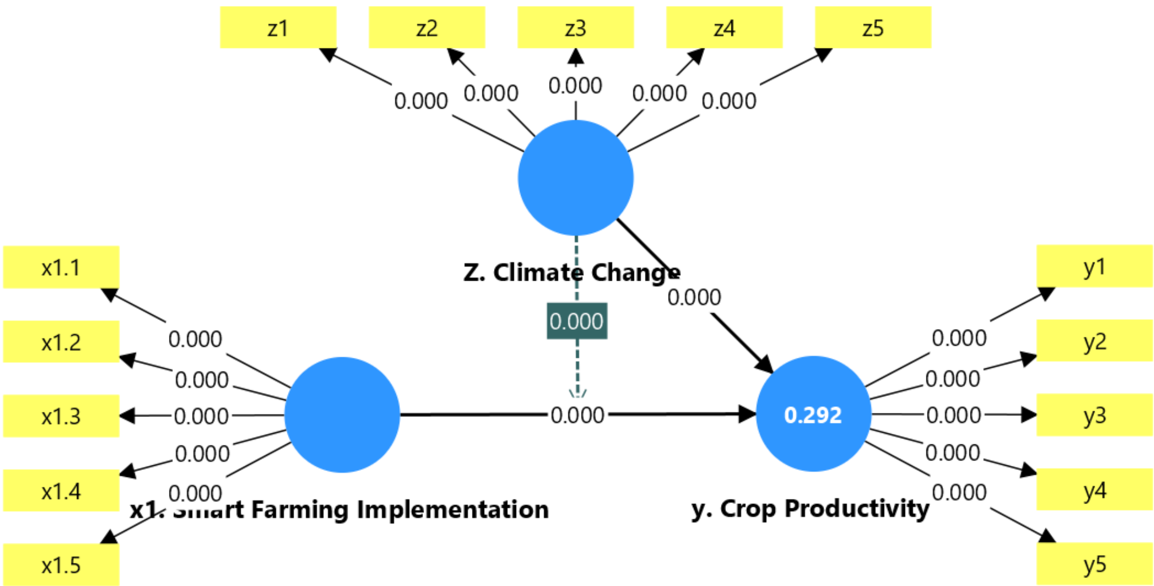

Figure 3. Path coefficients diagram

Table 4.6 Path coefficients

Hypothesis	Statement	Original Sample (O)	Sample Mean (M)	STDEV	T-Statistics	P-Values	Decision
H_1	Smart Farming Implementation has a positive effect on Crop Productivity.	0.305	0.312	0.059	5.148	0.000	Supported
H_2	Climate Change has a significant effect on Crop Productivity.	0.362	0.366	0.065	5.579	0.000	Supported
H_3	Climate Change moderates the relationship between Smart Farming Implementation and Crop Productivity.	0.280	0.280	0.068	4.100	0.000	Supported

The hypothesis testing results show that all proposed relationships in the structural model were statistically significant. H_1 is supported, indicating that Smart Farming Implementation has a positive effect on Crop Productivity ($\beta = 0.305$, $t = 5.148$, $p = 0.000$). This suggests that the higher adoption of smart farming practices, such as digital monitoring, automated irrigation, and technology-based pest control, is associated with incremental improvements in food crop productivity. H_2 is also supported, demonstrating that Climate Change has a significant effect on Crop Productivity ($\beta = 0.362$, $t = 5.579$, $p = 0.000$), highlighting that climate variability, including changes in temperature, rainfall patterns, and extreme weather events, exerts substantial pressure on agricultural productivity outcomes.

H_3 is supported, confirming that Climate Change significantly moderates the relationship between Smart Farming Implementation and Crop Productivity ($\beta = 0.280$, $t = 4.100$, $p = 0.000$). However, despite its statistical significance, the relatively small f^2 indicates that the moderating effect is context-dependent and conditional. Smart farming helps maintain or stabilize productivity under climate pressures but does not fully compensate for the structural impacts of climate change; it supports resilience rather than generating large deterministic gains in yield.

Overall, while all hypotheses are statistically supported, the path coefficients suggest that the effects of smart farming and climate change are minimal. This indicates that productivity improvements through digital technologies are incremental and highly dependent on agro-ecological conditions and farmers' capacity. It is important to note that this model is not intended as a comprehensive model of agricultural productivity but rather as an analytical framework to understand the relative role of digital technologies under climate pressure. In this context, smart farming functions as an adaptive instrument for sustaining productivity within climate-impacted agricultural systems rather than as a deterministic solution for maximizing yields.

4.4 Discussion

4.4.1 Smart Farming Implementation has a Positive Effect on Crop Productivity (H_1)

Hypothesis 1 states that the implementation of smart farming has a positive effect on crop productivity. The findings of this study confirm that the implementation of smart farming technologies contributes positively to improving food crop productivity in the region. However, although DOI and TAM explain adoption behavior, the moderate effect size observed in this study suggests that adoption alone does not automatically translate into substantial productivity gains, particularly when structural constraints such as land quality and capital limitations persist in the study area.

The moderate magnitude of the smart farming effect may also reflect uneven digital literacy, limited infrastructure, and partial adoption of technologies among Indonesian farmers, which constrain the full productivity potential of smart-farming systems. In this context, the local situation is used as a narrative backdrop to explain the observed effects rather than as a direct explanatory variable.

From a theoretical perspective, the findings still support the Diffusion of Innovations Theory (DOI), which explains that innovation adoption improves performance when the technology provides clear relative advantages and is compatible with users' needs. Smart farming systems offer tangible advantages through real-time monitoring, automated irrigation, and improved detection of crop diseases, thereby enabling farmers to make more accurate and timely decisions. In line with the Technology Acceptance Model (TAM), farmers are more likely to adopt smart farming practices when they perceive the technology as useful and easy to implement, leading to higher operational efficiencies and improved outputs. These theoretical frameworks strengthen the argument that technology adoption is not merely a behavioral change but a strategic decision that can directly enhance agricultural outcomes.

H_1: Smart Farming Implementation has a Positive Effect on Crop Productivity

4.4.2 Climate Change has a Positive Effect on Crop Productivity (H_2)

Hypothesis 2 states that climate change significantly affects crop productivity. The findings of this study confirm that climate change plays an important role in shaping crop productivity in Indonesia's agricultural sector. It is important to clarify that the positive path coefficient for H_2 does not indicate a beneficial effect on productivity. Rather, it reflects the strong influence of climate variability on farming outcomes, primarily by increasing the uncertainty, risk, and yield instability. In other words, the significant effect highlights the vulnerability of agricultural systems to climate change pressures rather than any productivity gain.

This result reflects the real conditions faced by food crop farmers, where changes in temperature patterns, rainfall variability, and the increasing frequency of extreme weather events directly affect the planting season, water availability, and crop growth stability. Farmers have increasingly experienced unpredictable planting schedules, drought periods, floods, and shifting rainfall intensities, creating instability in crop growth cycles. The significant path coefficient of climate change indicates that climate variability is a strong determinant of productivity outcomes, primarily by increasing uncertainty, risk, and yield instability.

From a theoretical perspective, this finding supports the Climate Risk and Vulnerability framework, which emphasizes that agricultural productivity is highly sensitive to environmental stressors such as rising temperatures and irregular precipitation. This also aligns with systems theory, which posits that productivity outcomes result from interactions between human systems (farming practices and management) and natural systems (climate and environmental conditions). By explicitly positioning climate change as a critical structural factor, this study reinforces the notion that productivity cannot be fully understood without considering environmental pressures.

This finding is consistent with previous studies that have shown that climate variability significantly affects agricultural outcomes. It highlights that rising temperatures, erratic rainfall, and extreme weather events can reduce global food production when adaptation strategies are insufficient. Similarly, technology-based adaptive tools help manage climate stress but do not eliminate the risks imposed by climate change.

In summary, H_2 captures the external climate pressure on crop productivity, whereas H_3 (examined separately) addresses the adaptive response of smart farming technologies to mitigate these pressures. This distinction clarifies that the significant effect of climate change reflects risk and vulnerability, not an automatic improvement in productivity.

H_2: Climate Change has a Positive Effect on Crop Productivity

4.4.3 Climate Change Moderates the Relationship between Smart Farming Implementation and Crop Productivity (H_3)

Hypothesis 3 proposes that climate change moderates the relationship between smart farming and crop productivity. The findings of this study confirm that climate change strengthens the role of smart farming as an adaptive mechanism to support crop productivity. This result reflects an important phenomenon in today's agricultural environment, where food crop production is increasingly challenged by unstable weather patterns, irregular rainfall, prolonged droughts and extreme climate events. Under such uncertain conditions, traditional farming practices are often unable to respond quickly and effectively, resulting in productivity loss.

Therefore, smart farming technologies provide incremental improvements by offering real-time data, automated systems, and decision support tools that help farmers manage uncertainty and mitigate risks, thereby maintaining more stable productivity levels. This finding also addresses a critical research gap, as many previous studies have examined the relationship between smart farming and productivity without explicitly testing climate change as a moderating factor. The significant moderating effect indicates a context-dependent contribution: the benefits of smart farming are not uniform across all environmental conditions but become more relevant and effective under higher climate variability, enabling farmers to respond more efficiently to environmental disruptions.

From a theoretical perspective, this result is consistent with Contingency Theory, which posits that operational effectiveness depends on the alignment between internal capabilities and external environmental conditions. In this context, smart farming represents an internal capability, whereas climate change constitutes external environmental pressure. The moderating effect suggests that smart farming becomes a more effective adaptive strategy when climate-related uncertainty is higher. This aligns with the Resource-Based View (RBV), where technology adoption serves as a strategic resource that enhances farmers' adaptive capacity. Smart farming tools optimize irrigation schedules, monitor soil moisture, and detect pest outbreaks early, thereby protecting crop productivity from climate stress.

These findings are supported by prior research. Aargue that climate change increases uncertainty in agricultural systems, making adaptive strategies and technological innovation essential for maintaining farming performance. Climate-smart agriculture improves yields and reduces climate-related vulnerability, demonstrating that technology-driven adaptation is more valuable under higher climate risks. Similarly, IoT-based smart farming systems, including sensor-driven monitoring and climate forecasting, help farmers mitigate the impact of extreme weather and make more informed decisions. Collectively, these studies reinforce that climate change not only directly affects productivity but also amplifies the adaptive role of smart farming, confirming its context-dependent contribution to crop productivity.

In practical terms, the moderation effect implies that farmers benefit most from smart farming technologies under conditions of high climate uncertainty, whereas policymakers should integrate smart farming initiatives with broader climate adaptation strategies, such as climate forecasting services, subsidies for digital farming tools, and training programs to strengthen technology-based climate resilience. Overall, the confirmation of H3 positions smart farming not only as a tool for efficiency improvement but also as an adaptive mechanism that supports incremental and context-dependent improvements in crop productivity in the era of climate change.

> *H_3:* Climate Change Moderates the Relationship between Smart Farming Implementation and Crop Productivity

4.4.4 Integrated Discussion of H_1, H_2, and H_3

Taken together, the findings indicate that climate change functions as a dominant structural pressure on agricultural productivity, while smart farming operates as an adaptive mechanism whose effectiveness increases under higher climatic stress but remains constrained by socioeconomic and agroecological factors. *H_1* states that smart farming adoption contributes to incremental improvements in crop productivity. However, the moderate effect size highlights that adoption alone is insufficient to achieve substantial gains, especially under structural constraints such as land quality, capital availability, and farmers' capacity to adopt. *H_2* confirms that climate variability strongly influences productivity outcomes, primarily by increasing uncertainty, risk, and yield instability.

This emphasizes that a statistically significant effect does not imply beneficial outcomes. *H_3* further shows that the role of smart farming as an adaptive mechanism is context-dependent, becoming more impactful when climate pressures are higher, thereby helping farmers maintain resilience rather than guaranteeing large productivity gains. Together, these results illustrate a dynamic system in which productivity emerges from the interplay between external climate pressures and internal adaptive strategies, mediated by environmental, socioeconomic, and technological conditions.

4.4.5 Conceptual Limitations
Although this study provides important insights, several conceptual limitations should be noted. First, the adoption of smart farming does not automatically equate to effectiveness; technology use may vary in intensity, quality, and alignment with farm needs. Second, climate change is a multifaceted phenomenon that cannot be fully captured by a single construct; additional environmental factors and local variability may influence productivity. Third, crop productivity should not be interpreted solely as a technical output, as it also depends on socio-economic, institutional, and market-related factors beyond technological interventions. Recognizing these limitations is essential for accurately interpreting the findings and guiding future research.

5. Conclusions

5.1 Conclusion

This study concludes that the implementation of smart farming has a significant yet moderate role in improving food crop productivity under increasing climate change pressures. The adoption of smart farming technologies, such as digital monitoring, automated irrigation, and technology-based pest detection, supports more efficient farm management and enhances farmers' capacity to respond to operational challenges. However, the magnitude of the effect indicates that smart farming functions primarily as an adaptive mechanism rather than a dominant driver of productivity growth.

The findings also confirm that climate change is a critical structural factor that shapes crop productivity by increasing uncertainty, risk, and production instability. Importantly, the significant interaction effect shows that climate change amplifies the relevance of smart farming, meaning that technology adoption becomes more valuable as climatic pressures intensify. This does not suggest that climate change improves productivity but rather that adaptive technologies are increasingly necessary to mitigate productivity losses and stabilize output.

Overall, this study highlights that smart farming should be understood not merely as an efficiency-enhancing innovation but as a strategic adaptation tool within climate-vulnerable agricultural systems. Therefore, efforts to strengthen food security in Indonesia should integrate smart farming initiatives with broader climate-adaptation strategies, including farmer capacity building, digital infrastructure development, and supportive agricultural policies.

5.2 Research Limitations

Despite these contributions, this study has several limitations. First, the cross-sectional research design limits the ability to capture the long-term and dynamic causal relationships between smart farming, climate change, and crop productivity. Second, the use of self-reported survey data may introduce response bias related to farmers' perceptions of technology adoption, climate conditions and productivity outcomes.

Third, the empirical focus on food crop farmers in Indonesia, particularly staple and horticultural crops, may limit the generalizability of the findings to other agricultural subsectors, such as plantations, livestock, or fisheries. Fourth, the model explains only part of the variation in crop productivity, indicating the influence of additional factors not included in the analysis, such as soil fertility, capital access, input availability, institutional support, and market conditions. Finally, climate change was measured based on farmers' perceptions rather than objective meteorological data, which may have reduced the measurement precision.

5.3 Suggestions and Directions for Future Research

Future research should adopt longitudinal or panel data designs to better capture the long-term effects of smart farming adoption on productivity under changing climate conditions. Expanding the scope of the analysis to other agricultural subsectors would help assess whether the adaptive role of smart farming varies across different production systems. Further studies should incorporate additional explanatory variables, such as soil quality, access to finance, farmer competencies, institutional support, and market integration, to enhance the model's explanatory power. Integrating objective climate data (e.g., rainfall, temperature trends, and drought indices) is also recommended to complement perception-based measures.

Finally, future research should explore alternative moderating or mediating factors, including digital literacy, innovation readiness, and farm management capacity, to better explain when and how smart farming translates into productivity and resilience gains. The author sincerely thanks all the respondents for their valuable participation in this study. Appreciation is also extended to the academic supervisors, colleagues, and institutions whose guidance and support contributed to the successful completion of this study.

Author Contributions

DS contributed to the study's conception and design, data analysis, and interpretation. She also played a significant role in drafting and revising the manuscript for intellectual content. JI assisted in the study's design, particularly in the data collection process, and contributed to the manuscript's writing and revision. MU contributed to the literature review, provided critical insights for the methodology, and helped with the manuscript's revisions. LL played a key role in the data analysis and interpretation, along with providing substantial revisions to the manuscript. MA assisted in the research methodology, participated in data collection, and provided significant feedback during the revision process. All authors have read and approved the final manuscript.

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