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The role of farmers and competence of extension workers in rice demonstration plots on the formation of smart farming perceptions in East Denpasar District

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***Abstract*---**Implementing smart farming is a strategic approach to boost agricultural efficiency amid land conversion and labor scarcity. In East Denpasar District, this modernization is facilitated through precision technology-based rice demonstration plots. This explanatory study aims to analyze the influence of farmers' roles and extension workers' competence on the effectiveness of rice demonstration plots and their implications for shaping farmers' perceptions of smart farming. The research areas were selected purposively in Subak Umalayu and Subak Umadesa. A total census method was applied, involving all 59 farmers within the demonstration areas as respondents. Data were analyzed using Structural Equation Modeling–Partial Least Square (SEM-PLS). The structural model results indicated that, directly, farmers' roles (coefficient=0.370; p-value=0.003) and extension workers' competence (coefficient=0.322; p-value=0.005) exerted a positive and significant effect on the success of the demonstration plots. Concurrently, the demonstration plots emerged as the most dominant factor directly driving smart farming perceptions (coefficient=0.523; p-value=0.000). Conversely, while internal farmers' roles and external extension competence failed to yield a direct significant impact on technological perceptions, both

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factors demonstrated significant indirect influences fully mediated through the performance of rice demonstration plots (full mediation). This research concludes that a paradigm shift toward computerized agriculture requires concrete empirical platforms—such as demonstration plots—to effectively bridge the digital divide. Therefore, upgrading technological training for extension officers and supplying inclusive tech-infrastructures for farmers are highly recommended.

***Keywords*---**digital agriculture, technology adoption, farmer perception, agricultural extension.

Introduction

The agricultural sector plays a crucial role in Indonesia's economy and food security. However, the sector currently faces numerous challenges, including climate change, decreasing agricultural land, labor shortages, and the declining interest of younger generations in farming activities. According to the Food and Agriculture Organization (FAO), the global population is projected to reach approximately 9.6 billion by 2050, requiring agricultural production to increase by nearly 70% to meet future food demands. If this increase cannot be achieved, the world may face severe food insecurity and food crises. In Indonesia, the agricultural sector also encounters structural problems such as land conversion, aging farmers, and limited technological adoption among rural communities. Younger generations tend to prefer employment outside agriculture due to perceptions that farming provides lower income, limited career opportunities, and physically demanding work conditions.

To overcome these challenges, innovation and modernization in agriculture are urgently needed. Agriculture is no longer viewed merely as traditional farming activities but has transformed into an integrated agricultural industry system involving input supply, production, processing, distribution, and marketing. In this context, modern agriculture emphasizes efficiency, sustainability, and optimal resource utilization. One of the most significant innovations in modern agriculture is precision agriculture, which focuses on the appropriate use of inputs based on crop requirements, environmental conditions, location, and timing. Precision agriculture aims to increase productivity while minimizing environmental impacts through efficient resource management.

The implementation of precision agriculture is closely associated with smart farming technology. Smart farming refers to the integration of digital technologies such as the Internet of Things (IoT), drones, sensors, Geographic Information Systems (GIS), satellite imagery, and data-based decision-making systems into agricultural activities. These technologies enable farmers to monitor soil conditions, crop growth, irrigation systems, fertilizer application, and pest management more accurately and efficiently. Smart farming also supports sustainable agriculture by reducing excessive use of fertilizers, pesticides, and water resources while improving productivity and product quality.

In Indonesia, the implementation of smart farming is still relatively limited and mostly concentrated in pilot projects and demonstration activities. One of the regions implementing smart farming programs is East Denpasar District, Bali. The agricultural sector in Denpasar has experienced significant land conversion over the last decade due to rapid urban development and tourism expansion. The decreasing area of agricultural land threatens rice production and food sustainability in the region. Consequently, the Denpasar City Agriculture Office, in collaboration with PT Pupuk Indonesia, introduced a smart farming-based rice demonstration plot program as an effort to improve agricultural productivity and efficiency.

The smart farming demonstration plot utilizes several modern technologies, including drones equipped with IoT systems, soil testing kits, and Normalized Difference Vegetation Index (NDVI) technology. Drones are used to apply nano fertilizers and monitor crop conditions efficiently, while IoT systems enable real-time monitoring of environmental and crop conditions. Soil testing kits help determine nutrient availability and soil quality, allowing more precise fertilizer recommendations. NDVI technology is used to assess crop health through satellite imagery. Through these integrated technologies, farmers can make better farming decisions and improve productivity while reducing operational costs and labor dependency.

The success of smart farming implementation is not determined solely by technological availability but also by human resource factors, particularly farmers' participation and agricultural extension workers' competence. Farmers play an essential role in adopting and implementing agricultural innovations. Their readiness, willingness, and active involvement in farming activities significantly influence the effectiveness of innovation adoption. Farmer participation includes preparing land, selecting seeds, applying fertilizers and pesticides, and participating in training and demonstration activities. Farmers who actively participate in demonstration plots are more likely to understand the benefits of smart farming technologies and develop positive perceptions toward innovation adoption.

In addition to farmers' roles, agricultural extension workers also contribute significantly to the success of smart farming implementation. Extension workers act as facilitators, educators, motivators, and communication bridges between technology providers and farmers. Their competence in technical agriculture, information technology, communication skills, social interaction, and administrative management determines how effectively they can assist farmers during the learning process. Competent extension workers are capable of simplifying technological concepts, providing practical guidance, and encouraging farmers to adopt new agricultural practices.

Rice demonstration plots function as participatory learning media where farmers can directly observe and experience the application of smart farming technologies. Demonstration plots provide opportunities for farmers to compare conventional farming methods with modern technological approaches. Through practical experience and observation, farmers can evaluate the effectiveness, efficiency, and benefits of smart farming systems. This participatory learning process contributes to shaping farmers' perceptions regarding the feasibility and usefulness of smart farming technologies.

Perception plays a critical role in technology adoption. Farmers' perceptions toward smart farming influence their willingness to implement and sustain technological innovations. Positive perceptions are generally formed when farmers believe that the technology is beneficial, easy to use, economically profitable, and compatible with their farming conditions. Conversely, negative perceptions may arise from limited understanding, high operational costs, lack of infrastructure, technological complexity, and uncertainty regarding benefits and risks.

Previous studies have demonstrated that farmer characteristics, extension support, and participatory approaches significantly influence agricultural technology adoption. Research by Hendri et al. (2022) found that farmers generally showed positive perceptions toward agricultural innovation programs when they perceived economic and operational advantages. Similarly, Johan (2022) reported that extension support and farmer characteristics significantly affected agricultural digitalization. However, studies specifically examining the influence of farmers' roles and extension workers' competence on smart farming perceptions through rice demonstration plots remain limited, particularly in Bali.

Therefore, this study aims to analyze the influence of farmers' roles and extension workers' competence on rice demonstration plots and their effects on the formation of smart farming perceptions among farmers in East Denpasar District, Denpasar City. The findings of this research are expected to provide practical and theoretical contributions to the development of smart farming implementation strategies in Indonesia. Furthermore, the study is expected to support policymakers, agricultural institutions, and extension agencies in improving agricultural modernization programs and strengthening sustainable agricultural development.

Material and Methods

This study employed an explanatory research design using a survey method to examine the influence of farmers' roles and extension workers' competence on rice demonstration plots and smart farming perceptions in East Denpasar District, Denpasar City. The explanatory approach was chosen because the study aimed to analyze causal relationships among variables and explain how farmers' participation and extension competence contribute to the formation of perceptions regarding smart farming implementation.

The research was conducted in Subak Umalayu and Subak Umadesa, East Denpasar District, Bali. These locations were purposively selected because they had implemented smart farming-based rice demonstration plot programs initiated through collaboration between the Denpasar City Agriculture Office and PT Pupuk Indonesia. The research was carried out over six months, from May to October 2024.

The study utilized both quantitative and qualitative data sources. Quantitative data included questionnaire responses and statistical analysis results, while qualitative data consisted of farmers' characteristics, perceptions, extension workers' roles, and field observations. Primary data were collected directly from farmers through interviews, questionnaires, observations, and documentation. Secondary data were obtained from journals, government reports, statistical publications, and documents related to smart farming programs.

The population of the study consisted of 59 farmers participating in the smart farming rice demonstration plot program in the selected subaks. Since the population size was relatively small, all members of the population were included as respondents using the census method. This approach ensured comprehensive data collection and minimized sampling bias.

The study examined four main variables: farmers' roles, extension workers' competence, rice demonstration plots, and smart farming perceptions. Farmers' roles were measured through indicators such as land preparation, seed preparation, fertilizer preparation, pesticide preparation, and labor readiness. Extension workers' competence was assessed based on farming competence, information technology competence, communication competence, socio-cultural competence, and administrative competence. Rice demonstration plots were evaluated through indicators including demonstration plot format, innovation characteristics, extension roles in demonstrations, farmer interactions, implementation timing, and demonstration costs. Smart farming perceptions were measured using indicators such as smart farming characteristics, technology adoption, infrastructure availability, operational costs, implementation barriers, and risk perceptions.

Data collection instruments consisted primarily of structured questionnaires using a Likert scale. The questionnaires were designed to measure respondents' perceptions and attitudes toward the variables studied. Additional information was collected through direct observation and interviews to strengthen data interpretation and contextual understanding. Data analysis was conducted using Structural Equation Modeling–Partial Least Square (SEM-PLS) with SmartPLS software. SEM-PLS was selected because it is suitable for analyzing complex relationships among latent variables and does not require strict assumptions regarding data normality or large sample sizes. The analysis included outer model evaluation, inner model evaluation, and hypothesis testing.

The outer model evaluation assessed the validity and reliability of measurement indicators using convergent validity, discriminant validity, Average Variance Extracted (AVE), composite reliability, and Cronbach's alpha. Indicators with loading factors above 0.70 were considered valid, while composite reliability and Cronbach's alpha values above 0.70 indicated reliable constructs.

The inner model evaluation analyzed the structural relationships among latent variables by examining R-square values and path coefficients. The R-square value measured the explanatory power of endogenous variables, while path coefficients indicated the direction and strength of relationships between variables. Hypothesis testing was performed using bootstrapping procedures with a significance level of 5% and a t-statistic threshold of 1.96.

This methodological approach enabled the study to comprehensively examine the direct and indirect relationships among farmers' roles, extension workers' competence, rice demonstration plots, and smart farming perceptions. The use of SEM-PLS also facilitated mediation analysis to determine whether rice demonstration plots mediated the relationships between independent variables.

Results And Discussion

Characteristics of Respondents

An empirical evaluation of the human components involved in the precision rice demonstration plots (demplots) in East Denpasar District requires a thorough baseline analysis of the farming population. In agricultural modernization research, socioeconomic parameters like age, education, land area, and experience determine how open farmers are to adopting digital tools.

1. **Age Distribution and Technical Implications**

The survey of 56 farmers participating in the Subak Umalayu and Subak Umadesa demonstration plots showed that 89.3% were in the productive age bracket of 15–64 years, while only 10.7% were 65 years or older. This demographic profile provides a solid foundation for digital transformation.However, deep qualitative interviews revealed a socio-technical gap: although the farmers are in their productive years, they are mostly in the upper edge of this range (45–60 years). This concentration creates a practical "digital divide" in urban subaks. While these middle-aged to older productive farmers have strong physical capacity for fieldwork, they show lower comfort levels with digital tools compared to younger generations.

2. **Farming Experience and Cognitive Resilience**

The data regarding farming tenure indicates a highly experienced sample: 44.60% of respondents had 21–30 years of farming experience, 25.00% had 31–40 years, and 19.60% had over 40 years. Only 10.70% had between 11 and 20 years of experience. This deep generational expertise creates an interesting psychological foundation for introducing smart farming. On one hand, decades of experience give farmers high cognitive resilience and intuitive mastery over local soil patterns, microclimates, and water distribution. On the other hand, it can lead to traditional biases. When smart farming systems introduce automated inputs via Internet of Things (IoT) sensors, experienced farmers often double-check digital alerts against their traditional observation methods.

3. **Land Scale and the Urban Gurem Challenge**

The structural landscape of East Denpasar is typical of urban agriculture, with 83.9% of respondents operating on tiny land sizes of less than 0.5 hectares. Only 7.1% managed between 0.5 and 1 hectare, and a small 8.9% controlled more than 1 hectare. This prevalence of smallholder farmers ("petani gurem") presents a major obstacle to technological expansion.

Modern precision tools—such as industrial agricultural drones and automatic rice transplanters—are designed for economies of scale. On tiny, scattered plots of under 0.5 hectares, the fixed capital costs of smart technologies make individual purchases unrealistic. Therefore, any successful expansion of smart farming in Denpasar cannot rely on individual purchases; it must use collaborative, shared models managed through Subak institutions.

4. Gender, Formal Education, and Professional Focus

The sample consisted entirely of men (100.0%), reflecting the intensive physical demands of land management and heavy machinery operations in Balinese rice cultivation. In terms of formal education, 14.3% had completed primary school (SD), 37.5% junior high (SMP), and 48.2% high school (SMA). While nearly half have a high school education, their primary exposure to digital systems remains limited to basic mobile messaging rather than specialized agricultural software. Additionally, only 42.9% relied on farming as their sole income source; 25.0% worked as construction laborers, and 32.1% held other urban jobs. This divided professional focus limits the time farmers can spend learning complex digital protocols.

Descriptive Analysis of Research Variables

To understand the structural model results, we first look at how respondents rated each variable using a 5-point Likert scale.

1. Farmer's Active Role (X1)

The overall mean score for the Farmer's Role was 3.17, placing it in the Moderate category. While indicators for field preparation—such as preparing land (X1.1, Mean: 3.50), procuring seeds (X1.2, Mean: 3.34), and distributing fertilizers (X1.3, Mean: 3.41)—scored relatively high, the scores for technological participation were much lower. Indicators assessing personal initiative in digital training (X1.5.1, Mean: 2.32) and experimental tech collaboration (X1.5.2, Mean: 2.52) fell into the Low category. This indicates that while Denpasar's farmers are highly competent in traditional field preparations, they take a passive approach to digital tool management, often expecting extension workers or tech providers to handle the hardware.

2. Extension Worker Competence (X2)

Extension Worker Competence earned an overall mean score of 3.52, putting it in the High category. Farmers gave high ratings to the workers' communication skills (X2.3, Mean: 3.59) and administrative consistency (X2.5, Mean: 3.63). However, a closer look at the data shows a clear skills gap: the indicator for technical mastery over digital systems and multi-crop data interfaces (X2.2, Mean: 3.45) was lower than their scores for traditional agronomic guidance (X2.1, Mean: 3.59). Field observations confirmed that many extension officers are comfortable explaining seed health or conventional fertilizer calculations, but face difficulties when troubleshooting IoT sensor modules or analyzing geo-spatial data files.

3. Performance of the Rice Demonstration Plot (Z)

The rice demonstration plot acted as the physical testing ground for these technologies and scored an overall mean of 3.39 (High/Moderate). The indicators for technology visualization—such as drone spraying demonstrations (Z2.1, Mean: 3.63) and mechanical rice transplanter performance (Z2.3, Mean: 3.70)—received some of the highest ratings. In contrast, items linked to personal risk and shared costs (Z6.1, Mean: 3.13) remained in the moderate zone. This reveals a pragmatic mindset: urban farmers enjoy watching the high-tech machinery work and appreciate the visible field results, but they express financial caution regarding the costs of keeping these systems running long-term.

4. Smart Farming Perception (Y)

The ultimate dependent variable, Smart Farming Perception, achieved a mean score of 3.48 (High). The data shows a split view among the farmers. They highly value the practical benefits (Y1, Mean: 3.65), recognizing that automated tools save water, optimize fertilizer use, and reduce labor requirements. However, their perception of risk (Y6, Mean: 2.45) scored quite low. This indicates that farmers view smart farming as an effective but risky approach, primarily due to the potential financial losses if the high-tech equipment breaks down.

Structural Equation Modeling (SEM-PLS) Analysis

The quantitative relationships between the variables were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) processed via SmartPLS software.

Evaluation of the Outer Measurement Model

Before testing the hypotheses, the measurement model was checked to ensure it met standard validity and reliability criteria:

1. Convergent Validity: The outer loading factors for all indicators exceeded the minimum required threshold of 0.50 (ranging from 0.612 to 0.884). The Average Variance Extracted (AVE) for all latent variables was well above the standard 0.50 limit: Farmer's Role (0.584), Extension Competence (0.611), Rice Demonstration Plot (0.642), and Smart Farming Perception (0.607).
2. Discriminant Validity: Cross-loading values confirmed that each indicator correlated most strongly with its own assigned variable. Additionally, the square root of the AVE for each construct was larger than its highest correlation with any other construct (Fornell-Larcker criterion).
3. Reliability Analyses: The Cronbach's Alpha and Composite Reliability scores for all constructs exceeded 0.70, demonstrating excellent internal consistency and measurement stability.

Evaluation of the Inner Structural Model and Hypothesis Testing

The structural path model measured the predictive power of the independent variables using the Coefficient of Determination (R-Square) and path coefficients (beta) tested via bootstrapping.

The model generated two distinct R-Square (R2) values:

1. R2 = 0.544 for the intermediate variable, Rice Demonstration Plot (Z). This indicates that the Farmer's Role (X1) and Extension Competence (X2) together explain 54.4% of the variance in demonstration plot success.
2. R2 = 0.612 for the final variable, Smart Farming Perception (Y). This confirms that the complete model accounts for 61.2% of the changes in how farmers perceive digital agriculture, which represents a strong predictive model.

Table 1
The table below summarizes the structural path coefficients and hypothesis testing results

Structural Path Connection	Path Coefficient (Beta)	T-Statistic	P-Value	Result Conclusion
Direct Effects:				
Farmer's Role (X1) -> Smart Farming Perception (Y)	-0.029	0.407	0.684	H1 Rejected (Not Significant)

Structural Path Connection	Path Coefficient (Beta)	T-Statistic	P-Value	Result Conclusion
Extension Competence (X2) -> Smart Farming Perception (Y)	-0.072	0.823	0.411	H2 Rejected (Not Significant)
Rice Demonstration Plot (Z) -> Smart Farming Perception (Y)	0.523	4.321	0.000	H3 Accepted (Highly Significant)
Farmer's Role (X1) -> Rice Demonstration Plot (Z)	0.370	2.987	0.003	H4 Accepted (Significant)
Extension Competence (X2) -> Rice Demonstration Plot (Z)	0.322	2.812	0.005	H5 Accepted (Significant)
Indirect (Mediation) Effects:				
X1 -> Rice Demonstration Plot (Z) -> Perception (Y)	0.194	2.891	0.004	H6 Accepted (Full Mediation)
X2 -> Rice Demonstration Plot (Z) -> Perception (Y)	0.168	2.710	0.007	H7 Accepted (Full Mediation)

Discussion of Hypotheses and Relationships

1. Direct Effects on Smart Farming Perception

The path analysis revealed unexpected results regarding direct structural relationships:

Hypothesis 1 (Farmer's Role -> Perception): The path coefficient was beta = -0.029 with a p-value of 0.684. Because the p-value is greater than 0.05, H1 is rejected. A farmer's internal role has no direct, immediate impact on their perception of smart farming.

Hypothesis 2 (Extension Worker Competence -> Perception): The path coefficient was beta = -0.072 with a p-value of 0.411. Since this is also non-significant, H2 is rejected. Verbal instructions and standard classroom training from extension workers do not directly improve technology perceptions.

These results highlight a significant practical problem. You cannot change a traditional farmer's mindset through theoretical lectures, pamphlets, or verbal explanations alone. Because farmers face real risks from urban land loss and fluctuating crop prices, they are naturally skeptical of technology. They do not automatically change their minds just because an extension worker talks about "Industry 4.0" or because they want to modernize.

2. Direct Effects on Demonstration Plot Success

In contrast, the paths leading to the physical demonstration plots showed strong, positive results:

Hypothesis 4 (Farmer's Role -> Rice Demonstration Plot): The path coefficient was beta = 0.370 with a p-value of 0.003, confirming H4.

Hypothesis 5 (Extension Worker Competence -> Rice Demonstration Plot): The path coefficient was beta = 0.322 with a p-value of 0.005, confirming H5.

These findings prove that the physical success of a high-tech demonstration plot requires both internal cooperation from farmers and technical support from extension workers. The plot cannot succeed without the farmer's local knowledge in preparing the soil and managing irrigation. At the same time, it relies on the extension worker to coordinate schedule changes, manage tech sponsors, and enforce quality control standards.

3. The Critical Role of the Demonstration Plot

Hypothesis 3 (Rice Demonstration Plot -> Smart Farming Perception): The path coefficient was beta = 0.523 with a p-value of 0.000. This highly significant relationship strongly supports H3.

The demonstration plot emerged as the most powerful direct driver of perception change in the entire model. This confirms that smallholders in Denpasar are highly experimental and visual learners. They need to see a technology working successfully in a real field before they trust it. Watching an agricultural drone fly over Subak Umalayu to spray nano-fertilizer, or seeing a mechanical rice transplanter plant rows evenly in Subak Umadesa, provides the immediate proof farmers need. The empirical evidence of saved labor and uniform growth breaks through their initial hesitation far better than any theoretical discussion.

4. Mediation Analysis: The Vital Role of Full Mediation

Hypothesis 6 (Farmer's Role -> Plot -> Perception): Showed a significant indirect effect (beta = 0.194, p-value = 0.004), supporting H6.

Hypothesis 7 (Extension Competence -> Plot -> Perception): Showed a significant indirect effect (beta = 0.168, p-value = 0.007), supporting H7.

Because the direct paths from farmers and extension workers to perception were non-significant, the demonstration plot acts as a full mediator. This full mediation pattern is a key insight of this research. It proves that the demonstration plot is an essential bridge for communication. Without a well-run physical plot, any individual effort by a farmer or advice from an extension worker fails to change community perceptions.

The demonstration plot serves as a translation tool: it takes complex digital ideas (like IoT, big data, and drone maps) and transforms them into clear agricultural outcomes that farmers understand (such as lower costs, faster planting, and higher yields). For urban subaks facing modern land pressures, well-organized demonstration plots are the most effective way to introduce digital agriculture.

Conclusion

Based on the results of the data analysis, structural equation modeling (SEM-PLS), and detailed discussion regarding the transition to digital agriculture in East Denpasar District, the following conclusions can be drawn:

1. Farmer's Active Role (X1) and Extension Worker Competence (X2) have no direct, statistically significant effect on the Smart Farming Perception (Y) of urban smallholders. Theoretical lectures, verbal guidelines, and administrative training do not immediately alter farmers' mindset or reduce their perceived risks concerning high-tech capital investments.
2. Farmer's Active Role (X1) and Extension Worker Competence (X2) have a strong, positive, and statistically significant direct effect on the physical success of the Rice Demonstration Plot (Z). The practical operational achievement of a precision agricultural plot depends heavily on combining the farmers' traditional on-field experience with the extension workers' technical assistance and coordination.
3. The Rice Demonstration Plot (Z) has a highly significant, positive direct effect on Smart Farming Perception (Y). The physical plot serves as the primary engine for mindset transformation, providing visual and empirical proof—such as uniform plant growth and immediate labor reduction—that successfully overcomes the smallholders' economic skepticism.
4. The Rice Demonstration Plot (Z) acts as a Full Mediator for both exogenous variables. This structural pattern proves that any internal initiative from farmers or capacity building from extension workers must be channeled through a concrete, functional field demonstration plot. Without this practical bridge, direct attempts to influence or modernize urban farmers' technical perceptions will fail due to the existing digital divide and localized risk aversion.

Recommendations

Based on the conclusions above, several strategic recommendations are proposed to support the digital transformation of urban agriculture:

1. For the Department of Agriculture (Dinas Pertanian): Future funding and agricultural development programs should pivot away from classroom-based lectures. Instead, resources should be heavily allocated to sustaining physical, localized demonstration plots within individual Subaks to allow continuous, hands-on learning.
2. For Extension Workers (Penyuluh): Training programs for extension officers must be upgraded to focus on technical troubleshooting, IoT interface calibration, and geo-spatial drone mapping, ensuring they can confidently guide farmers during active field demonstrations.
3. For Subak Institutions: Given the small, fragmented land ownership (under 0.5 hectares), Subak leaders should establish communal asset-sharing protocols. This will allow individual smallholders to access modern tools, such as agricultural drones and automatic transplanters, through collaborative utilization rather than high-risk individual purchases.

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